

Harnessing Artificial Intelligence: Risk Assessment and Sustainable Business Model Pathways for the Industrial Sector

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Abstract

The global industrial sector is a highly polluting and greenhouse gas-emitting sector. As industries increasingly explore Artificial Intelligence (AI) to enhance operational efficiency and drive innovation, questions emerge regarding its alignment with sustainability objectives. While AI is often positioned as a key enabler of digital transformation, its sustainable integration into industrial operations remains fragmented and fraught with risk. This thesis investigates how AI deployment in the industrial sector—specifically within secondary industries such as machinery and manufacturing—poses sustainability risks, while also presenting opportunities for sustainable business model innovation. Drawing on an extensive literature review and semi-structured interviews with industry stakeholders, the study identifies six key sustainability risk areas linked to AI integration: energy consumption and carbon emissions, hardware and e-waste, inequalities and workforce displacement, privacy and cybersecurity, bias and programming and regulatory developments. The research highlights a gap in comprehensive risk frameworks tailored to industrial applications of AI, as well as a lack of alignment between existing AI-enabled business models and sustainability principles. The study proposes pathways for responsible AI adoption through business model innovation that mitigates these risks while leveraging AI's potential for sustainable value creation. These include green AI and AI-as-a-Service, circular AI hardware management, inclusive AI upskilling platforms, ethical AI certification services and privacy-first AI solutions. By embedding AI into operations, products, and services in a manner that is both strategic and ethically sound, industrial firms can better balance digital transformation with long-term sustainability goals. Ultimately, this thesis contributes to the emerging discourse on AI governance by offering practical recommendations for risk-informed AI integration and catalyzing the development of sustainability-driven frameworks for the industrial sector.

Keywords: artificial intelligence, industrial sector, sustainability risks, sustainable business models, risk assessment

Executive Summary

The industrial sector faces significant sustainability challenges on both environmental and organizational fronts. The complex and dynamic conditions under which these firms operate entail aligning new technologies with corporate sustainability goals and social responsibilities. Companies must navigate complex supply chains, manage regulatory compliance, and ensure workforce skills and governance are updated. In short, firms need strategies that achieve business goals while also addressing sustainability constraints and expectations.

Industry 4.0 and the broader wave of digital transformation are reshaping the industrial sector. New technologies such as artificial intelligence (AI) promise major gains in efficiency and flexibility but also carry significant implications for sustainability. AI plays a dual role in this sustainability landscape. As an enabler, AI systems can analyze data to improve energy efficiency, predict maintenance needs to avoid breakdowns, optimize logistics to reduce emissions, and improve circularity. AI can also support decision-making and unlock efficiencies across value chains. However, AI also introduces risks. Training and running sophisticated models often require vast computing power, driving up electricity use and potentially increasing carbon footprints. AI systems may rely on rare minerals and generate electronic waste when hardware is upgraded. Moreover, the automation that AI entails can have social impacts like workforce displacement, and unchecked efficiency gains can trigger rebound effects. Ethical and security issues such as biased algorithms, data privacy breaches, or operational failures can also undermine sustainability outcomes. Understanding both the promises and the challenges of AI is central to strategic decision-making and risk management.

This thesis examines how industrial firms can balance these outcomes and transform AI technologies into sustainable innovations. The research sets out to bridge a critical knowledge gap at the intersection of AI integration, sustainability risks and business model pathways. It aims not only to identify and contextualize the sustainability risks of AI within industrial settings but also to propose actionable pathways using Sustainable Business Model (SBM) foundations to guide companies in mitigating those risks. The key research questions (RQs) include:

RQ1: How does the integration of AI pose sustainability risks for industrial companies?

RQ2: How can industrial companies develop AI-enabled business models that align with sustainability principles?

A qualitative and exploratory research design is used to explore these questions. A systematic literature review consolidates existing knowledge on AI, risk, and sustainability in the industrial sector, while also mapping out theoretical concepts and fundamental frameworks of risk assessment and management. Two primary stakeholder groups were consulted through semi-structured interviews: Group 1, composed of sustainability and innovation professionals from the industrial sector, and Group 2, comprising technical experts and strategists of AI and sustainable AI integration. This dual perspective allows the study to explore a wide range of insights and identify areas of alignment and divergence between sustainability and digital innovation practitioners. The analysis of data from the literature review and interviews identifies themes and patterns that inform the development of a risk assessment and broader findings.

The findings revealed that AI systems introduce sustainability risks that are not adequately addressed in most corporate strategies. The study identified six key sustainability risks associated with industrial AI systems:

1. **Energy Consumption and Carbon Emissions:** AI models—especially those utilizing large datasets or deep learning algorithms—are energy-intensive, contributing to increased electricity usage and associated carbon emissions, particularly when deployed at scale.
2. **Hardware and E-Waste:** The physical infrastructure required to support AI, including sensors, edge devices and servers, contributes to increased material throughput, premature obsolescence, and the global e-waste crisis.
3. **Inequalities and Workforce Displacement:** Automation facilitated by AI may lead to job displacement, disproportionately affecting low- and middle-skilled workers. This risk is exacerbated when reskilling and upskilling programs are inadequate or unevenly distributed.
4. **Bias and Programming:** Algorithmic bias can perpetuate or amplify social inequities, especially in industrial applications. These risks often stem from biased training datasets and opaque development processes.
5. **Privacy and Cybersecurity:** The data-centric nature of AI introduces new privacy and security vulnerabilities. In industrial settings, where sensitive operational and employee data is used, this risk is particularly acute.
6. **Regulatory Developments and Uncertainty:** Evolving AI governance regimes pose compliance challenges and create uncertainty around liability, data governance, and ethical use, especially for multinational firms operating across jurisdictions.

The qualitative sustainability risk matrix revealed that privacy and cybersecurity, inequalities and workforce displacement and energy consumption were perceived as the most significant threats due to their high likelihood, broad impact, and relevance to stakeholder concerns.

To address the identified risks and operationalize sustainability principles within AI deployment, this study proposes five AI-specific SBM pathways. Each strategy is grounded in four value pillars—transparency, stakeholder engagement, modularity, and partnerships—identified as essential for integrating sustainability into AI-enabled business models. These pathways extend traditional SBM frameworks by incorporating the characteristics of AI and are designed to transform risks into innovation opportunities. Green AI and AI-as-a-Service (AIaaS) models prioritize energy efficiency through model optimization techniques like compression and federated learning. Partnering with green-certified data centers allows companies to reduce their carbon footprint and Scope 2 and 3 emissions. Circular AI Hardware Management promotes a closed-loop system for hardware reuse and promotes recycling reduce material waste. Companies can offer take-back programs, refurbishment incentives, and loyalty rewards for returning end-of-life devices. Inclusive AI Upskilling Platforms assess the workforce impacts of AI and co-create upskilling programs with educational institutions and NGOs to equip employees with future-proof skills, such as system maintenance, data stewardship, and critical thinking. Ethical AI Certification Services entail third-party certifications to validate a company’s commitment to bias mitigation, fairness, and data protection. Modular toolkits for self-assessment can also be used internally. Privacy-First AI Solutions include tools that ensure data minimization, decentralized data processing, and explainable AI. Such offerings respond to growing stakeholder demand for transparent and secure AI systems.

The discussion reveals that the sustainability risk assessment of industrial AI systems is deeply shaped by the unique characteristics of industrial manufacturing firms, which are capital-

intensive, operationally focused, and increasingly committed to embedding sustainability strategically. These companies face mounting external pressures from evolving regulations, driving greater transparency and accountability around AI adoption. While AI offers promising opportunities to optimize operations and reduce sustainability impact, the emerging risks create significant challenges. The sector experiences a tension between rapid technological enthusiasm and incomplete understanding of AI's sustainability implications, resulting in fragmented approaches and organizational blind spots. Moreover, the current governance frameworks often treat AI and sustainability separately, underscoring the need for integrated, systemic AI governance that embeds long-term sustainability goals, transparency, and stakeholder inclusion.

This thesis offers several actionable recommendations for industrial companies, AI developers, policymakers, and academic institutions to ensure the responsible and sustainable integration of AI into industrial systems:

Integrate AI Sustainability Risks into Core Sustainability Processes. Companies should evaluate AI-related sustainability risks—such as energy use, workforce displacement, and data privacy—alongside other material issues in sustainability reporting, auditing, and strategy development. Cross-functional collaboration between digital and sustainability teams is critical to avoid siloed decision-making.

Adopt Proactive Governance and Life Cycle Assessment (LCA). Firms must develop streamlined life cycle assessment tools tailored to digital technologies to quantify environmental trade-offs. Establishing task forces to assess sustainability throughout AI's development and deployment can help anticipate and mitigate risks.

Embed Sustainability in Procurement and Transparency Standards. Companies should include sustainability criteria such as energy efficiency, explainability, and data ethics in AI procurement contracts and supplier evaluations. Investing in explainable AI is essential for transparency in high-stakes industrial applications.

Design Sustainable AI Solutions from the Ground Up. AI developers should integrate energy efficiency and ethical design into the software development lifecycle using tools like model compression and edge computing. Providing real-time sustainability metrics to clients can offer a competitive advantage and foster informed use.

Advance Policy for Sustainable and Accountable AI. Policymakers should embed environmental and social impact requirements into AI legislation and certification schemes. Public funding should support research that examines AI's broader effects on energy systems, labor, and ecosystems.

Build Capacity Through Interdisciplinary Education and Research. Academic institutions should design curricula that integrate sustainability, ethics, and AI development. Researchers should pursue longitudinal studies and standardized tools to evaluate AI's sustainability impacts, particularly in real-world industrial settings.

By implementing these recommendations, stakeholders and the larger industrial sector can move from reactive compliance toward strategic, sustainability-driven innovation, ensuring that AI contributes to just and resilient industrial transformations. The study highlights a dual imperative for organizations to manage both the sustainability of AI—its direct environmental and social impacts—and sustainability for AI, meaning how AI can support broader sustainability transitions. Overall, the research points to an industrial sector in transition, balancing innovation, regulation, and sustainability with evolving knowledge, emerging risks, and opportunities for responsible AI adoption.

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Abbreviations

AI	Artificial Intelligence
AIaaS	AI-as-a-Service
B2B	Business-to-Business
CBAM	Carbon Border Adjustment Mechanism
CSDDD	Corporate Sustainability Due Diligence Directive
CSRD	Corporate Sustainability Reporting Directive
DT	Digital Twin
EU	European Union
IBL	Integrated Bottom Line
LCA	Lifecycle Assessment
ML	Machine Learning
RM	Risk Matrix
RQ	Research Question
SBM	Sustainable Business Model
SBTi	Science-Based Targets Initiative
TBL	Triple Bottom Line

1 Introduction

Digital transformation has had an unprecedented impact on virtually every sector across the globe, influencing individuals and institutions. It refers to the process of rewiring an organization to deploy technology at scale, with the objective of creating and capturing value. Though the nature and nuance of this transformation are heavily debated, there is scholarly consensus that digital transformation affects consumer decision-making and in turn, necessitates organizational adaptation (Paul et al., 2024). It is thus no surprise that digital transformation has become a priority within organizations, as well as a characterizing feature of this decade.

The integration of digital solutions is particularly evident within the industrial sector. The industrial sector converts materials into finished goods through manufacturing processes and transformative operations such as assembly and machining (Szirmai, 2012). It entails an industrial base, wherein, through a combination of managerial and manufacturing processes, businesses engage in critical activities that are of extractive, servicing and manufacturing natures (Stephens, 1980). As of 2023, the industrial sector contributes to approximately 27 percent of the global economy (Statista, 2025). These businesses have significant impacts on the environment through exploitative actions such as the over-extraction of minerals, overconsumption of raw materials like water and energy and the mishandling of waste. The industrial sector—namely the manufacturing subsector and its related value chains—is also responsible for an estimated 30 percent of the world’s greenhouse gas emissions (World Economic Forum, 2024). The IPCC placed the industrial sector as the most polluting end-use sector in its 5th Assessment Report, beating out sectors such as transport and buildings.

There are several key sustainability challenges that pose a threat to humanity: rising global population, misinformation and mishandling of data, resource depletion and climate change, technological inequality, federal corruption and regional/global conflicts (Yigitcanlar & Cugurullo, 2020). In general, the global environmental crisis is thus putting pressure on industries to develop sustainable practices. While making sustainability-related trade-off decisions, they require a multi-objective lens to understand the risks, constraints and feasibility of a project. Traditional industrial systems entailing manual processes, fixed automation methods and reactive maintenance are struggling to address the complex dynamics of modern production environments. Consequently, digitized solutions such as Artificial Intelligence (AI) are now at the forefront of innovative sustainability strategies.

While there is still no strongly accepted definition of the term ‘AI’, it can generally be defined as a sub-discipline of digitized sciences dealing with data processing and performing functions normally associated with human intelligence (Peres et al., 2020). More specifically, an AI-trained entity is meant to possess three main capabilities: (1) learn from acquired information, (2) understand data and extract conclusions and (3) make unsupervised decisions and handle uncertainty (Cugurullo, 2020). There are several types of AI that possess different levels of capabilities and development (see Figure 1).

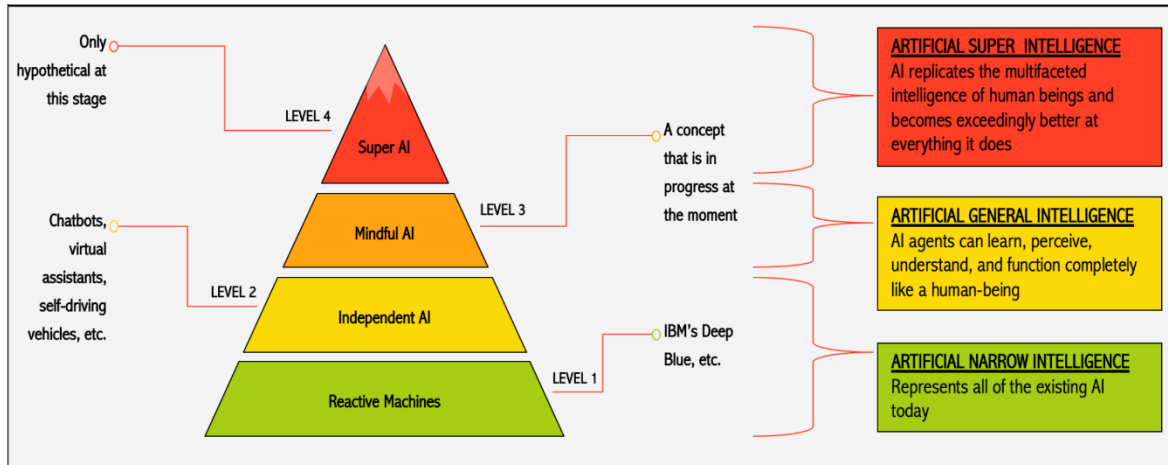


Figure 1. Types of AI (Yigitcanlar & Cugurullo, 2020).

Industry 4.0—known as the Fourth Industrial Revolution—has coined the term ‘Industrial AI’. Industrial AI is a “systematic discipline, which focuses on developing, validating and deploying various machine learning (ML) algorithms or industrial applications with sustainable performance” (Lee et al., 2018, p. 1). It is an interdisciplinary solution for industrial applications, combining machine learning, natural language processing and robotics (See Figure 2). Some of its core capabilities include planning, forecasting, innovation and uncovering insights (Shah et al., 2024). AI can be used as a tool for demand and generation forecasting, optimized storage, predictive maintenance, pricing and theft detection (Li et al., 2023).

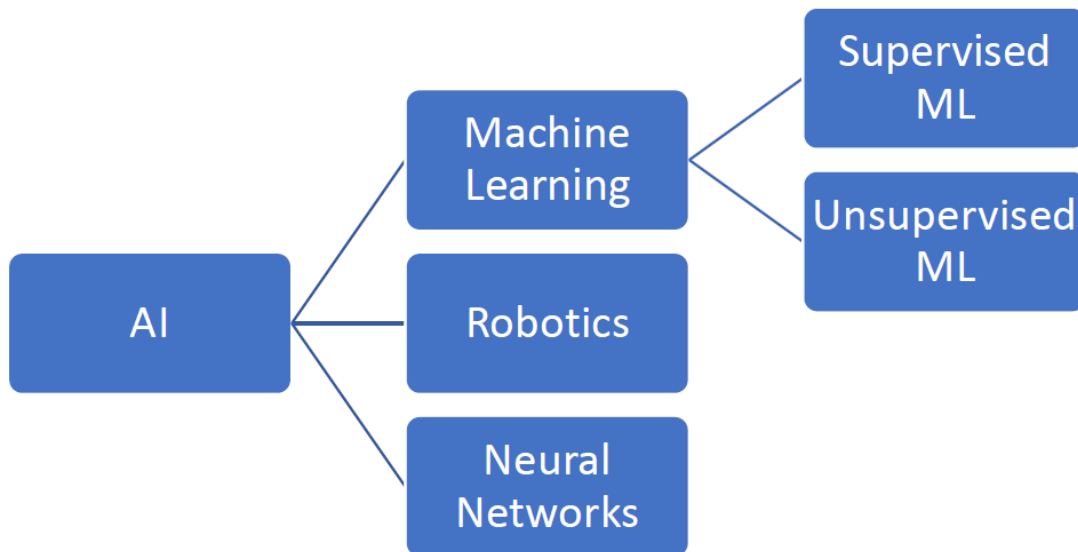


Figure 2. Subsets of AI (Sena & Nocker, 2021)

Industry 4.0 shifted the paradigm of value-capture, production and consumption through digital transformation, underscoring AI as a key tool in optimizing industrial processes. It is important to note, however, that the use of AI is perceived critically. The deployment of AI within the industrial sector remains low (Peres et al., 2020). In fact, scholars believe that industries do not perceive AI as a tool for sustainability, but rather one to serve optimization (Ahmad et al., 2022). While around 35 percent of manufacturing companies use AI (Andre, 2024), nearly 80 percent of companies lack the knowledge or capacity to use it (DC Velocity, 2024).

1.1 Background

It is only recently that lawmakers are recognizing the importance of regulating the deployment of AI. In 2024, the European Parliament brought into force the AI Act—the first global and binding horizontal regulation of AI—which provides a risk-based approach and framework for the use and supply of AI systems (Madiega, 2024). It seeks to foster a transparent, secure, sustainable and traceable development pathway for AI technologies. The United States is developing a comparable regulatory framework to mitigate potential risks emerging from the use of AI applications (Somer & Thalmann, 2023). These regulations focus on end-users and consumer safety. What is currently lacking are regulations that consider risks in operations and processes, especially within industries.

This uncertain climate has dictated the sporadic development of AI within the industrial sector, especially for sustainability. While 36 percent of industrial companies (in the United States) are concerned about the compatibility and integration of AI, the larger worry is that AI on its current developmental trajectory will potentially displace at least 50 percent of the workforce around the globe (Ahmad et al., 2022). This is especially because AI can reduce human intervention and make corresponding decisions across the supply chain, from raw material procurement to distribution. The lack of guidelines for integrating AI in the industrial sector enhances a company's risk of failure in business growth, especially considering technical, privacy and security risks (Rana et al., 2022). Furthermore, AI faces numerous challenges in terms of process automation technology, versatility and data quality. This includes difficulty in establishing AI networks with large stores of current data, employee training requirements, integration issues in legacy systems, human worker resistance etc. (Ahmad et al., 2022). Moreover, if AI algorithms are trained incorrectly, they may perpetuate biased recommendations and inaccurate results, thus also bringing in ethical consequences (Nishant et al., 2020).

Ahmad et al. (2022) posit that AI outperforms traditional energy technologies in areas such as controllability, big data handling, cybersecurity and attack prevention and maintenance prediction. Ahmad et al. (2022) also cite workplace safety, root cause analysis, smarter workforce, human error detection, yield enhancement, lower operational costs, easier identification of product defects, supply chain efficiency, better product design and quick decision making as advantages of using the tool. From an economic perspective, AI modeling offers flexibility and more reliable data processing at a cheaper rate compared to conventional modeling technologies and methods (Olabi et al., 2023).

Haben and Young (2023) emphasize that AI can be utilized in the design stages, to consider alternative methods, new equipment, new plants to enable different fuels and to reduce waste. Additionally, they state that AI could be used to improve carbon accounting and modeling. However, while AI might optimize one aspect of energy, it might undermine another. For example, AI may lead to reduced energy use in a company, but it requires significant emissions to operate at all. Jha et al. (2024) note that AI is a major contributor to Scope 3 emissions. These unintended consequences are salient in hindering its adoption, especially for companies establishing robust decarbonization roadmaps.

Industrial companies are failing to create an AI-based sustainable development agenda due to integration problems. While AI in the industrial sector is currently being used for cleaner production, carbon capture and smart manufacturing, it has not been fully realised as a sustainability tool. Rather, it is seen as a process optimizer. It is imperative to note that AI is currently applied to augment human performance and not replace it, which will ostensibly hold true in the future (Peres et al., 2020).

1.2 Problem Definition

A comprehensive review by Tripathi et al. (2024) underscores the need for a balanced approach to AI deployment, while Nishant et al. (2020) list risk reduction as a crucial challenge if implementing AI for sustainability. Despite these calls to action, there is still a notable lack of comprehensive risk assessments for AI in industrial applications (Somer & Thalmann, 2023). Given the high-stakes decision-making, critical operations and the complex nature of the industrial sector, an extensive inquiry into the challenges, unintended consequences and rebound effects of deploying AI in industrial settings is pivotal to its uptake.

Though AI is considered an important tool for advancing sustainability, it is still far from being a catalyst for sustainability-driven business models at a global level (Calabrese et al., 2023). There is a concern that if companies reorganize their business models to integrate AI, traditional players may have the upper hand, due to factors such as a slow rate of market adoption (Burström et al., 2021). Burström et al. (2021) state that configuring AI-based delivery would require identifying and developing new capabilities and employee competencies. AI innovation forces manufacturers to become accountable for servicing their own AI-enabled equipment, implying that R&D departments will have to start improving the longevity of wearable parts and reducing downtimes (Qvist-Sørensen, 2020).

This shift requires a rethinking of traditional business models that depend on revenue from maintenance services and parts. In fact, most benefits generated by AI to businesses are contingent on changes made to business models (Sena & Nocker, 2021). Sena and Nocker (2021) also stress that though business model innovation is highly relevant to AI, the relationship between the two is understudied. The new digital transformation paradigm presents AI as an enabling technology. However, while AI is especially relevant for business-to-business (B2B) contexts, the industrial sector is yet to establish a comprehensive framework and roadmap to guide AI integration into their business models and operations (Peres et al., 2020)

While AI's role in sustainability and the risks it presents to sustainability are well-explored, these risks have not been explicitly contextualized within the industrial sector. More specifically, the applications of AI and risks posed by AI to the industrial sector are limited to technological narratives. For example, associated sustainability risks such as increased energy and water use have not been contextualized within the industrial sector. The opportunities for AI-driven business models are fragmented. Further, there appear to be clashing notions of AI in the industrial sector, leading to perception-based risks. These factors seem to be pivotal reasons for its slow uptake within the industrial sector, despite its high potential.

Although AI solutions are inherently technical, their success will be determined by how effectively they navigate and influence psychological, sociological and organizational factors (Nishant et al., 2020) that currently impede human progress in this area.

1.3 Research Questions and Objectives

The integration of AI in the industrial sector remains limited and lacks multi-departmental application. Though there is scepticism surrounding the perfectness of AI as a tool, the consensus across the literature is that AI will play a pivotal role in transforming not just the industrial sector, but society at large (Li et al., 2023; Shah et al., 2024). There is a need for these businesses to transform their technology, while simultaneously expanding their networks to collaborate with innovative enterprises (Burström et al., 2021; Leone et al., 2021). An exploratory study is thus key and poses a necessity to evaluate the connections between the risks of implementing AI and industrial business models.

This thesis looks to expand the current narrative of AI by outlining a path for it to be integrated into operations, products and services in the industrial sector sustainably. The aim is to put forward observations to aid in navigating the intersection of AI, sustainable business models and risk management within the industrial sector. The main objective is to assess the sustainability risks of AI in the industrial sector and develop business models for its responsible adoption.

Thus, I propose the following research questions (RQs) for my thesis:

- 1. How does the integration of AI as a tool pose sustainability risks for industrial companies?**
- 2. How can industrial companies develop AI-enabled business models that align with sustainability principles?**

RQ1 entails a comprehensive assessment of various risks falling under various sustainability dimensions. This includes the identification, analysis and recommendation to mitigate said risks so that industrial businesses can make more informed decisions while implementing AI in their processes. This study focuses on 6 key sustainability risks—energy consumption and carbon emissions, hardware and e-waste, inequalities and workforce displacement, privacy and cybersecurity, bias and programming and regulatory developments.

RQ2 entails the examination of existing sustainable business model concepts as well as the exploration of novel sustainable business model proposals that can integrate AI in a manner that mitigates the identified sustainability risks while leveraging AI as a tool. It focuses on the more responsible use of AI to address digital transformation, while also achieving sustainability goals within an organisation.

The two research questions were addressed by conducting a comprehensive literature review as well as interviews with multiple actors. The data collected was embedded into a synthesis matrix and analysed for emerging themes, narratives and patterns. Based on the findings, the study has conceptualised several avenues for industrial businesses to take while integrating AI as a tool for sustainability.

1.4 Scope and Limitations

The ‘industrial sector’ is an expansive term and covers a diverse set of businesses. This study largely considers the secondary industry (for example, machinery, equipment, production), and specifically firms that generally focus on manufacturing and processing. Thus, it will ignore functions such as extraction and commerce. This study centers around process-oriented AI, rooted in machine learning and structured data applications. This does not cover AI systems such as language models. Additionally, the focus does not extend to the hypothetical technical developments of AI but rather focuses on its current potential. Additionally, the growth of AI is both rapid and sporadic while also navigating a complex regulatory environment. Given these ever-changing dynamics, some angles may not be fully captured in this study. Furthermore, the risk assessment captures the six key risks more commonly discussed in interviews and supported by literature. This is by no means an exhaustive list and is based on the data collected specifically for this research. It is also important to distinguish between a ‘risk’ assessment and an ‘impact’ assessment. This study will not consider the impacts of AI on society, but rather how the use of AI poses risks to the company.

1.5 Ethical Considerations

This study adheres to ethical research principles that facilitate the fair and responsible treatment of participants, stakeholders and data. The interviewees gave written consent to use the contents of the discussion for this paper (See Appendix I). They were given the freedom to refuse to answer questions and to withdraw at any time without any consequence. Additionally, they were briefed and debriefed prior to and after the interview, respectively, to ensure ethical treatment (See Appendix II). To ensure transparency, they were informed of how the data collected would be used and shared in the context of writing this thesis. Along with these considerations, the name of the interviewee, their organization and/or any other identifying characteristics were not disclosed in the final analysis.

Further, the research upholds academic integrity and responsible data handling practices. Sources have been carefully cited, and any AI-generated insights have been critically examined but not accepted unconditionally. Careful consideration has been given to avoid biases and perpetuating potentially negative narratives that would affect said stakeholders. The study follows guidelines on non-maleficence¹ and ensures that the findings do not encourage the exploitative or unsustainable use of AI. Additionally, the study has taken measures to avoid promoting overly optimistic or alarmist perspectives and instead present an objective analysis.

1.6 Audience

The findings can encourage responsible AI innovation in industrial companies by identifying opportunities for integration within operations, products and services. Novel applications and sustainable business models will allow a smoother integration of AI and provide actionable insights. This can help companies achieve a dual objective of leveraging AI while minimizing negative sustainability impacts. The research can also help industrial businesses make informed and strategic decisions to balance AI advancement with their sustainability agenda by addressing the challenges and risks associated with deploying AI. It can serve as a guide for risk assessments related to the sustainability implications of AI integration.

The thesis can shed light on the broader implications of utilizing AI in the industrial sector. Revealing the risks and challenges of integrating AI in businesses can encourage AI compliance frameworks, fostering the ethical and transparent use of AI that aligns with global sustainability principles. Ultimately, this can catalyse regional and national level regulations to facilitate a better environment for AI integration.

For academic audiences, this thesis contributes to the growing body of interdisciplinary research at the intersection of artificial intelligence, industrial innovation, and sustainability. It offers a conceptual framework and practical insights that can inform future empirical studies and theoretical developments in sustainable technology adoption. By critically examining the risks of AI integration in industrial settings and sustainable business model pathways, the research supports ongoing scholarly discussions around responsible innovation, corporate sustainability, and digital transformation. It may serve as a foundation for further inquiry into governance mechanisms, impact assessment methodologies, and sector-specific case studies related to AI and sustainability.

¹ The Northwest Association for Biomedical Research defines the principle of non-maleficence as ‘obligation not to inflict harm intentionally’.

1.7 Disposition

This thesis is divided into six chapters. Each chapter builds toward a comprehensive analysis that will inform the integration of AI as a sustainability tool in the industrial sector.

Chapter 1 sets the foreground of the study, by defining the problem, establishing the background and presenting the main objectives and scope of the thesis.

Chapter 2 explores relevant theories, concepts and frameworks, as well as current knowledge related to risk assessment, sustainable business models and AI in the industrial sector.

Chapter 3 establishes the research approach and design by explicating the methods for data collection and analysis.

Chapter 4 presents the result of the research by framing the context and outlining the identified risks and sustainable business model pathways that are relevant to the aims of the study.

Chapter 5 interprets the results presented in the previous chapter by providing a deeper evaluation of the implications of the risks, as well as the sustainable business models.

Chapter 6 reflects on the objectives of the research, summarizes the findings of the study and suggests directions for further research and practical applications.

2 Literature Review

This chapter is divided into two sections. The first explores the foundational concepts of risk assessments and sustainable business models, while the second examines the current relevant knowledge surrounding AI and sustainability in the industrial sector. These observations underpin the findings of this thesis. The observations from this section also shape the final analysis of this study.

2.1 Theories and Conceptual Frameworks

2.1.1 Risk Management and Assessments

‘Risk’ is seen as a singular unit that has two notable characteristics: (1) the probability of an event’s occurrence and (2) the associated magnitude of its occurrence (Pearce et al., 1981). The identification of risks traces back to the Ancient East, primarily within agriculture and social development (Kiseleva et al., 2018). The capacity to assess risks was first recorded 2400 years ago in Athens, but has only been recognized as a scientific field for a few decades (Aven, 2016). In these years, risk management practices have been pervasive in virtually every field, so much so that the rapid uptake of risk management practices has been noted as a social phenomenon (Mikes, 2009). Aven (2016) reports that the risk field generally falls into two functions: (1) performing generic research for the development of frameworks, concepts and theories and (2) using assessment and management to study and inform the decision making of a project. Hopkin (2018) states that there are four types of risks—hazard risks, opportunity risks, compliance risks and control risks. This is different from the distinction of risks made by Wolke (2017), who posits that business risks can be divided into financial risks and performance risks. Kiseleva et al. (2018) provide a high-level dichotomy of risks, citing that there are external and internal risks that occur due to external conditions and internal factors of an organization.

Risk management is an integrated approach aimed at evaluating, controlling and monitoring these risks (Hopkin, 2018). Financial institutions notably use risk techniques to address capital inadequacy and the allocation of capital within business units, popularizing it as a financial tool (Mikes, 2009). However, this does not account for non-aggregated or non-quantifiable risks, such as strategic failure, environmental risks and operational risks. As a result, ‘holistic’ risk management emerged to address these. Holistic risk management is the process by which an organization identifies, manages and adapts to threats within its management structure, by expanding the range of risks beyond that which is ‘insurable’ and ‘fortuitous’ (Davies & Bain Hogg, 1997).

Options for risk management are ideally evaluated through an integrative and/or iterative procedure (Robinson & Levy, 2011). This is where risk assessment plays a pivotal role. Risk assessment is the nucleus of risk management and is used by organisations to steer said risks (Wolk, 2017). It is not interchangeable with the concept of risk management, but rather a subset (See Figure 3). In theory, risk assessment influences research decisions because it ‘provides a highly organized profile of the current state of knowledge of particular issues and systematically elucidates scientific uncertainties’ (National Research Council et al., 1994, pp. 27-28).

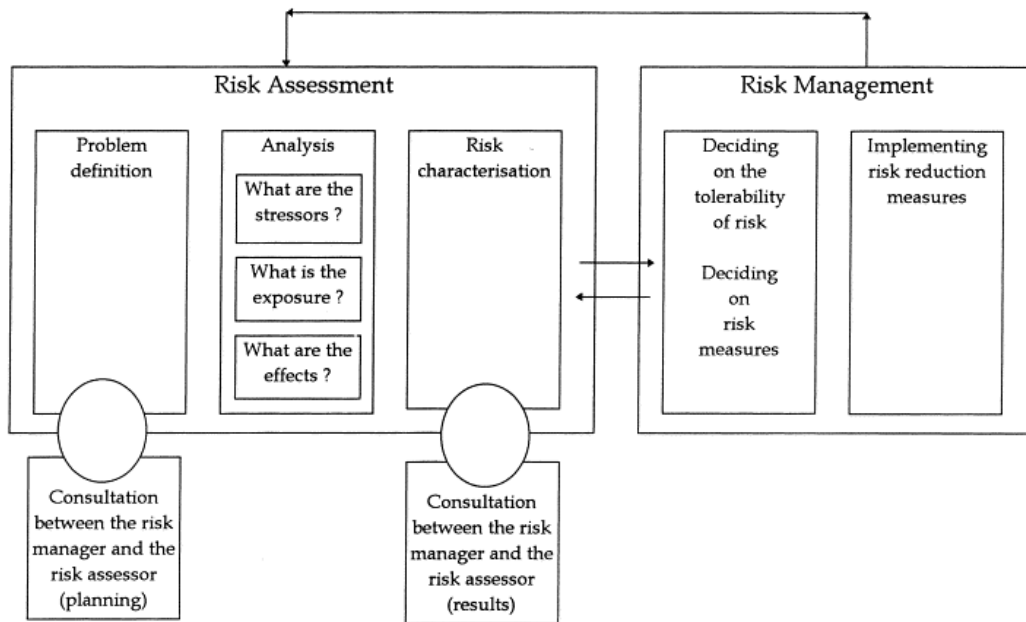


Figure 3. Link between risk assessment and risk management [redrawn by Eduljee (2000) based on the Health Council of the Netherlands, 1995].

The National Research Council published a revolutionary report in 1983², describing a four-step process for risk assessment (National Research Council et al., 1994). This included hazard identification, dose-response assessment (assessment of variations and in response, susceptibility), exposure assessment and risk characterization. While this framework provides a strong foundation for the risk assessment process, it ignores important aspects of holistic risk management, such as the relationship between science and policy, as well as stakeholder engagement (Power & McCarty, 2002). Yet, even in an evolving environment, risk assessment remains a fundamental framework for the systemic evaluation of a risk associated with an industrial activity (Zio, 2018).

Risk assessment aids in organizing knowledge available on events, scenarios and processes to affect decision-making pertaining to risk management (Zio, 2018). For it to be useful, risk assessments need to

...provide traceable information for arguing the decisions; the risk assessment outcomes must be communicated in a way that allow the decision makers to interpret them properly for their purposes and to understand the associated uncertainty related to the available knowledge used for the assessment (Zio, 2018, p. 179).

This decision-making mechanism not only evaluates the risk but also tries to understand the extent to which the organization can take it on and whether the predicted return will validate the corresponding risk (Kiseleva et al., 2018). Thus, risk assessment justifies the undertaking of tasks while providing guidance for neutralizing risks. Businesses act on the knowledge of potential threats and vulnerabilities by formulating strategies that protect their interests (Patil et al., 2012).

Sustainability and Risk Assessment

² The 1983 NRC report formerly titled ‘Risk Assessment in the Federal Government: Managing the Process’ established a framework for risk assessment within the US federal government.

Many of the business risks that are deemed as urgent in the current climate (such as supply chain disruptions, regulatory changes and brand value) can be directly linked to sustainability challenges (Schulte & Hallstedt, 2017). Krysiak (2009) thinks beyond this and posits that risk is an inevitable aspect of sustainability. Yet, it is often neglected in the discourse of these issues. This can also be taken a step further to say that sustainability as a framework itself entails the assessment of decisions, because its very core lies in futurity (Krysiak, 2009). While there are firms that analyse sustainability risks for ethical purposes, most of them do it for business reasons such as reducing sustainability risk costs, leveraging competitive angles and improving reputations (Anderson, 2006). This perspective is reiterated by Schulte & Hallstedt (2018), who attempt to further the discussion by providing three steps for integrating a strategic sustainability perspective into risk management: (1) identification of sustainability effects in internal and external stakeholder value, (2) proactive inclusion of sustainability in objective settings across the organization hierarchy and (3) development of concrete support to identify, assess and manage sustainability risks.

Gibson (2006) outlines several key assertions to keep in mind while conducting a sustainability risk assessment. He stated that sustainability is comprehensive and encapsulates socio-economic as well as biophysical factors that are interrelated. To add on, precaution while handling sustainability problems is needed, given that its effects occur in dynamic and multi-scalar systems. The minimization of negative effects is not enough and should encourage larger efforts towards sustainability. And finally, actions should take on a multi-objective lens and enforce positive feedback loops (Gibson, 2006).

Existing Frameworks

Sustainability risk assessments in the industrial sector tend to take a lifecycle assessment (LCA) approach. For example, Palousis et al. (2008) developed a comprehensive sustainability risk assessment (SRA) framework specifically for the product design stage, wherein they integrated Life Cycle Analysis and Activity-based Life Cycle Costing with risk assessment to model the impact of sustainability risks. The SRA framework takes an integrated bottom line (IBL) perspective. While the triple bottom line (TBL) gives equal importance to the economic, social and environmental dimensions³, and considers sustainability impacts on each dimension separately, the IBL integrates the dimensions into a single performance metric and evaluates them based on their financial impact. A multi-level framework was proposed by Gargalo et al. (2016), who also use risk assessment in early-stage design, but focus on techno-economic and environmental sustainability. They establish a process of quantifying economic risk, environmental risk and environmental impact categories to identify trade-offs and ultimately implement a quantitative and qualitative assessment of sustainability decisions.

Ahmad & Wong (2018) conducted a systematic literature review of existing sustainability assessment frameworks in the manufacturing sector, citing that while the environmental dimension is well-examined, it is not adequately linked to economic and social viewpoints. They concluded that there is a need to focus the assessments on the process level and emphasize the TBL perspective more. In a similar vein, Krysiak (2009) does not prioritize just one aspect and presents a higher-level framework, wherein they link risk management and sustainable development using the fairness-based criterion. They elucidate on the idea that a decision can be considered sustainable if it improves the utility of current generations without making other generations worse off. The fairness-based criterion has undergone various criticisms—fairness

³ The Triple Bottom Line (TBL) was coined by John Elkington in 1994. It encompasses a framework that assesses a company's performance based on three dimensions: social, environmental, and economic. It is often represented as "People, Planet, and Profit". The intention was to encourage businesses to consider their broader impact beyond just financial gain.

does not have a universal definition, biodiversity considerations are overlooked and resource allocation can be inefficient (de Herve, 2022; Schmid et al., 2021).

2.1.2 Sustainable Business Models

The concept of a business model is an abstract portrayal of the interactions between value flow and value elements in a business (Nosratabadi et al., 2019). These elements influence value proposition, creation, delivery and capture. This is also underscored by Evans et al. (2017), who consider ‘value’ to be the underpinning of business models. They note, however, that value may not mean the same thing to everyone in every context. Porter & Kramer (2011) bring forth the concept of ‘shared value’, wherein economic value can be generated in a way that also fosters societal value by tackling its challenges. This is meant to drive innovation and productivity by reframing the addressal of societal challenges as a competitive advantage to a firm.

Globalization and the push to keep up with sustainable development goals and principles have made the business environment more complex. From this angle, business model innovation has been identified as a potential mechanism to integrate sustainability into businesses (Evans et al., 2017), and hence, the alternative solution of a ‘sustainable’ business model has emerged. Geissdoerfer et al. (2018) have presented a working definition of SBMs as a “business model that incorporates proactive multi-stakeholder management, the creation of monetary and non-monetary value for a broad range of stakeholders, and which holds a long-term perspective” (p. 409). Sustainable business models (SBMs) are meant to empower businesses to meet sustainable development goals while simultaneously achieving productivity and profitability goals (Nosratabadi et al., 2019). In other words, creating value for the triple bottom line becomes the ultimate objective. Knudson (2023) adds to this, stating that integrating the three dimensions of sustainability along with long-term outlooks and stakeholder engagement within a business requires the business to understand how its resources, operations and relationships interact and create value. While business model innovation is suspected to yield higher returns compared to innovations of products and processes, SBMs provide the advantage of higher risk mitigation and resilience, yielding higher diversification and opportunities for value co-creation (Geissdoerfer et al., 2018).

The way that SBMs are conceptualized is heavily influenced by stakeholder relations, which in turn influences the way a firm is governed as well as its overall behaviour (Nosratabadi et al., 2019). While SBMs are not always achieved through technological development and service innovation (Nosratabadi et al., 2019), it is what is dictating the current industrial climate. Industry 4.0 points to more dynamic business networks rather than restrictions within a single company, by means of using networked manufacturing, self-organizing adaptive logistics and customer-integrated engineering (Prause, 2015). Industry leaders are transforming their relationships by adopting a longer-term view—leading to more expertise in a networking environment with regard to innovation, product development, intellectual property and risk (Prause, 2015). This leads to a more complex, open and evolutionary mode of progress.

Stubbs & Cocklin (2008) have posited several key attributes that can guide organizations in developing mature SBMs:

- Framing sustainability as a strategy by itself
- Utilizing the triple-bottom-line reporting method for measuring and communicating progress such as the Global Reporting Initiative (GRI)
- Fostering a stakeholder-integrated view of the organization

- Embedding sustainability into top management to ensure percolation into organizational processes and culture

Prause (2015) proposes three general archetypes of SBMs that are relevant in the current climate—open innovation models, service design models and e-residency for Industry 4.0. These have been summarized in Table 1.

Table 1. Summary of SBMs proposed by Prause (2015)

Type	Description
Open Innovation Models	Open innovation leverages both internal and external knowledge sources to accelerate innovation. Enabled by digital networks, it fosters collaborative value creation beyond firm boundaries, integrating users, enterprises, and virtual communities. Challenges include managing intellectual property risks, especially from user-contributed data, which may jeopardize patentability and innovation sustainability.
Service Design Models	Service design models focus on customer-centric, sustainable solutions by emphasizing the value of service over the product. It illustrates how customization, traceability, and product returns can support circular economy goals. Industry 4.0 technologies expand these models to complex, cross-company supply chains.
E-residency for Industry 4.0	E-Residency offers digital identities for global entrepreneurs to manage location-independent businesses online. A cyber-administrative platform can support companies in Industry 4.0 by enabling remote management of information and value flows in supply chains. It facilitates international business through digital governance, market access, and integrated smart supply chain operations.

2.2 Current Knowledge

2.2.1 AI and the Industrial Sector

AI technologies often act as enablers in the industrial context, by perceiving the environment, processing acquired data and solving complex problems (Peres et al., 2020). They also have an adaptive capability of learning from experience to improve specificity for functions. Javaid et al. (2022) posit that industrial AI is a transformative tool for Industry 4.0. Industrial AI aids in realizing and maturing resilient industrial systems by enabling them to be fault-tolerant, on-demand and self-organizing (Lee et al., 2019). Industrial AI thus becomes highly relevant, in

that it facilitates the development, deployment and maintenance of varied forms of AI solutions for industrial applications (Peres et al., 2020).

Javaid et al. (2022) provide a brief overview of the current functions of industrial AI, beginning with how it allows producers to supply generative materials at a faster rate through robotic cooperation. Manufacturers use industrial AI for sensor data analysis, predictive maintenance, repair and servicing, failures and downtime detection. They go on to mention that industrial AI facilitates the digital twin (DT) technology, allowing assessments of the manufacturing process, wherein quality problems and output issues are analyzed. The DT technology is a virtual model or ‘copy’ of a physical entity, which is interconnected through the exchange of data in real time (Singh et al., 2021). DT allows producers to clearly understand the use of products and allows for the refilling process to be automated. Lee et al. (2018) state that there are four enabling technologies for AI in the industrial sector. These have been summarized in Table 2 below:

Table 2. Enabling Technologies for AI in the Industrial Sector (Lee et al., 2018)

Technology	Function
Data Technologies	Enable successful acquisition of relevant data with key performance metrics across dimensions. It interacts with manufacturing resources to transfer and store data from machines and factories to the cloud, therefore enabling communication between the physical space and cyber space.
Analytics Technologies	Converts data from critical components into relevant information. Its modeling reveals patterns, correlations and other information that would otherwise be unknown in manufacturing systems. This is especially useful for machine prognostics and health management.
Platform Technologies	Provide hardware architecture for storage, analysis and feedback of data. This also provides compatibility for data analysis which is vital in understanding machine characteristics such as processing power, agility etc.
Operation Technologies	Enables decision making based on extracted information. It enables machines to provide insights and communicate. Machine-to-machine interactions also become possible and thus improve decision making.

Peres et al. (2020) establish five dimensions in which industrial AI is distinguished within the broader field of AI:

1. Infrastructure: Hardware and software emphasize real-time processing, industrial-grade reliability, high security and interconnectivity.
2. Data: Characteristics of data include large volumes, high velocity, high variety and diverse sources.

3. Algorithms: Physical, digital and heuristic knowledge are integrated, along with highly complex model development, management, deployment and governance.
4. Decision-making: The industrial setting dictates a low tolerance for error and gives high importance to uncertainty handling and efficiency for large-scale optimization issues.
5. Objectives: Value creation is addressed through factors such as scrap reduction, quality improvement, augmented operator performance and accelerated ramp-up times.

Barriers related to the application of AI indeed include data security and cybersecurity concerns, lack of understanding of the principles of AI technology, difficulty in refitting existing systems and quantifying the economic benefits of AI (Li et al., 2023).

2.2.2 The Sustainability of Industrial AI

To understand the debate surrounding AI and sustainability, it is first crucial to explore what AI can do for sustainability. AI presents huge opportunities to reorganize industrial processes through the lens of sustainability. Nishant et al. (2020) state that these pathways are seen with various sustainability dimensions.

From an environmental perspective, sustainability in manufacturing can significantly reduce the consumption and wastage of resources while also improving their utilization and mitigating pollution (Kar et al., 2022). This also includes green transportation networks, crash predictions and better supply chain management. This is supported by Nishant et al. (2020), who cite minimization of waste, reduction in energy consumption, recycling improvements and industrial symbiosis as some of the many sustainability advantages that AI has to offer.

With regard to smarter energy management, AI can be used as a tool for demand and generation forecasting, optimized storage, predictive maintenance, pricing and theft detection (Li et al., 2023). Given that many big industrial players have committed to net-zero targets and are developing decarbonization roadmaps, AI has the potential to open up multiple pathways towards decarbonization in this sector.

Many decarbonization solutions for the industrial sector are expensive and often require significant upgrades or redesigns of existing equipment/plants (Haben & Young, 2023). However, Olabi et al. (2023) and Haben and Young (2023) point out that if AI is used as a low-carbon technology, it decreases costs and space while increasing efficiency. Additionally, if 45 percent of work processes were to incorporate AI, it could lead to annual cost savings of up to two trillion US dollars globally (Burström et al., 2021). AI can aid in inference and tracking the source of emissions at potentially more granular levels than currently monitored (Haben & Young, 2023). There is a strong correlation between AI deployment and reduced carbon emissions, insinuating that AI development can aid in optimizing the structure of industrial development (Ding et al., 2023). This also implies that AI can help in achieving the dual goals of high output against low pollution. AI is also vital for water management, as pointed out by Nishant et al. (2020). ML systems can predict stream flow and evaluate water quality parameters. Biodiversity solutions are also developing using AI, to predict public opinion, model social media data, estimate ecosystem services, model habitat suitability and availability and more.

Nishant et al. (2020) emphasize that AI gives firms a chance to execute holistic solutions for sustainability issues, which are free from the self-interest and ulterior motives of individuals and organizations. They go as far as to say that developing AI functions for sustainability is a justified investment and should become a priority to improve performance outcomes. While this sentiment is somewhat shared by van Wynsberghe (2021), they contrast this notion by also arguing that AI has unintended consequences on sustainability goals, which can pose a risk to businesses. Therefore, they contend that there is a distinction to be made between AI for

sustainability versus the sustainability of AI. This is, in fact, the most pivotal consideration for the sustainability of AI. AI as a technology may present opportunities for advancing sustainability and yet may hinder the same path to progress for sustainability in other aspects.

AI places great importance on ML models and algorithms to understand how machines perceive and analyze data. Naturally, this leads to scholars like Kar et al. (2022) pointing to cyber privacy and security concerns—such as AI biases, personal autonomy and unemployment risks—as threats that need to be addressed by companies adopting AI. Because using AI requires the data from multiple stakeholders in different formats and structures, decisions taken by AI occur in a ‘black box’⁴, which can sometimes lead to inaccurate results, and even fail in life-or-death type scenarios, limiting transparency and public trust (Yigitcanlar & Cugurullo, 2020). While siloed approaches can minimize these risks, they are often inefficient and not adequately effective (van Wynsberghe, 2021). These are extremely important considerations because responsible AI is dictated by an intersection of transparency, fairness and privacy (See Figure 4) (Radanliev, 2025).

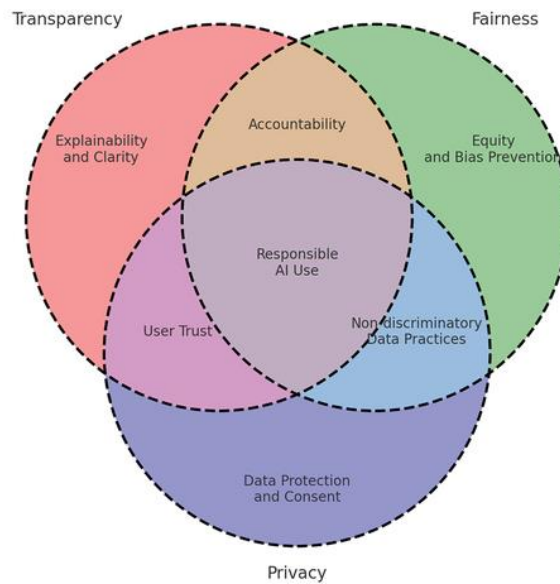


Figure 4. Ethical Considerations in AI Development (Radanliev 2025)

The application of AI also sees huge energy consumption levels and an increased carbon footprint, which creates direct rebound effects for a business. From a sustainability perspective, Qvist-Sørensen (2020) brings up that while AI might optimize one aspect of energy, it might undermine another. For example, AI may lead to reduced energy use in a company but requires significant emissions to operate at all. In fact, Jha et al. (2024) have noted that AI is a major contributor to Scope 3 emissions. In fact, a single AI model training can lead to carbon emissions equivalent to the lifetime of five cars (van Wynsberghe, 2021). These unintended consequences are salient in hindering its adoption, especially for companies establishing robust decarbonization roadmaps.

Water consumption is also a huge detriment from a sustainability lens. It uses water for cooling servers that power computation functions for AI and for energy production (Gupta et al., 2024). Gupta et al. (2024) claim that water consumption by big technology companies’ data centers is

⁴ In the context of AI, a ‘black box’ refers to an AI system or model whose internal functioning, decision-making processes, and underlying rationale are not transparent. Users can input data and receive output, but they lack insight into how the system arrived at the conclusion.

severely underestimated and cite that Microsoft's Dutch data center was fourfold their initial calculations. In fact, training AI at the level of computation of humans in a year can cost 126,000 litres of water (Gupta et al., 2024). It is often the case that data centers are located in already water-scarce areas, thus exacerbating the issue and furthering existing inequalities (George et al., 2023).

These unintended consequences often extend to social dimensions. As highlighted by Galaz et al. (2021), equal access to AI does not necessarily equate to equal or fair outcomes. Given that companies tend to externalize their costs to mitigate risks, this can undermine the incentive for AI developers to implement responsible principles.

The consensus surrounding the sustainability of AI is in a state of disarray. While many scholars affirm that AI has negative effects on the environment and society, Kopka & Grashof (2022) claim that it is still debatable whether AI is a crucial part of environmental sustainability issues. Thus, it is important to fully determine the potential of Industry 4.0 technologies before deploying them for sustainability activities (Kar et al., 2022). While there are solutions emerging to calculate the sustainability of software applications, these have not been adopted or scaled up in the context of AI (van Wynsberghe, 2021).

Van Wynsberghe (2021) attempts to formulate a definition for 'sustainable AI' as a movement to foster change in the entire lifecycle of AI products (i.e., idea generation, training, re-tuning, implementation, governance) towards greater ecological integrity and social justice (p. 1). They underscore that sustainable AI is specifically concerned with the larger sociotechnical system of AI. Yigitcanlar & Cugurullo (2020) identified key areas of improvement for sustainable AI— stakeholder engagement, transparency and trust, technological agility, regulatory action and ethical development. With all of this, the true value of AI for sustainability will only be realized on a macro level.

3 Research Design and Methodology

This chapter delves into the conceptualization of this thesis by following the rationale behind its design. It will cover the approach to the research as well as the methods in which data for the thesis was collected and analysed.

3.1 Research Design

To investigate the dynamics, perceptions, narratives and contexts of the themes in this study, a qualitative approach was taken in the research. Qualitative methods are well-suited for capturing experiences and garnering a holistic understanding of the research. However, the legitimacy of qualitative research is often undermined at the expense of quantitative research methods, as the latter is perceived to be more objective and thorough (Vishnevsky & Beanlands, 2004). Yet, theories surrounding AI are rarely unidimensional, and qualitative research methods follow a naturalistic paradigm (Lincoln & Guba, 1985). Rather than assuming that empirical evidence can reveal the truth, this study will consider that the truth is not predetermined but formulated by actors.

The qualitative research approach is defined by an exploratory study. Exploratory studies are generally undertaken with the objective of understanding a phenomenon or situation under study. They are especially useful when trying to interpret cyber systems (technosocial behaviours) (Edgar & Manz, 2017). Additionally, they are well-suited to answer broader or comparatively open-ended research questions. There are various types of exploratory studies—longitudinal, ecological, case control etc. This particular thesis employs a cross-sectional outlook, wherein a sample is collected from an entire population at a specific period in time (Edgar & Manz, 2017), offering a picture of characteristics and narratives relevant to that time frame. This is differential to experimental studies which manipulate variables during the study and can better determine cause-effect relationships (Wang & Cheng, 2020).

This thesis employs two key methods of data collection—a literature review and interviews. While the literature review was instrumental in developing the theory and conceptual framework for this study, both methods were useful for formulating the risk assessment and subsequent discussion.

3.2 Data Collection

3.2.1 Literature Review

It is critical to examine observations made by existing literature. The consideration of existing narratives, theories and prior relevant research is essential for research projects. This method is especially suitable when context and interpretation by stakeholders are central to the research question (Rogelberg, 2008). This especially aligns with the exploratory nature of the study. To ensure a comprehensive and structured approach to this method, the data collection for the literature review consisted of a three-step protocol: (1) source identification, (2) search string development and (3) criteria formulation.

Source identification was the first step in this process and involved the identification of credible sources to obtain relevant literature. The primary databases selected included but were not limited to Google Scholar, SCOPUS, JSTOR and ResearchGate, which offer access to peer-reviewed articles and conference proceedings. Further, government, corporate and technical reports were utilized to capture an industry and market perspective. Supplemental information came from white papers and industry and policy briefs, strengthening academic findings with practical applications.

Once the relevant sources had been identified, a set of well-defined search strings was developed using Boolean operators (AND, OR etc.). These strings included terms related to AI, sustainability risks and sustainable business models and industrial applications. Some key search queries included

(“Artificial Intelligence” OR “AI-driven”) AND (“sustainability” OR “ESG”) AND (“industrial sector” OR “manufacturing”)

(“AI and Circular Economy”) OR (“AI-driven business models”)

(“Risk assessment” OR “sustainability risk frameworks” OR “ethics”) AND (“AI” OR “artificial intelligence”)

These search strings were refined iteratively based on preliminary findings to enhance the relevance of retrieved documents.

Upon application of the search strings, a total of 436 articles were collected. To refine the data meant for analysis, a set of inclusion and exclusion criteria was established (See Table 3).

Table 3. Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
<ul style="list-style-type: none"> -Published in peer-reviewed sources -Relevance to AI, sustainability risks and business models, and industrial applications -Published in the last five years* 	<ul style="list-style-type: none"> -Non-English publications (if translation is not available) -Opinion pieces -Irrelevant sectors and/or functions

*While the inclusion criterion was a five-year time frame, some older sources were used due to limited recent literature on certain topics or the continued relevance of foundational frameworks.

Once the selection criteria were applied to the collected articles, the total number of articles for analysis was refined to 72.

3.2.2 Interviews

While the literature review can account for the opinions and consensus of the scientific community, it can fail to capture certain nuances of those outside of academia. Thus, interviews can act as a complement to this method. Interviews allow participants to provide contextual descriptions of events and opinions (Byrne, 2001). For this research, it is integral that perceptions of AI related to sustainability and sustainable business models are thoroughly captured (See Appendix III and IV). Semi-structured interviews provide the benefit of giving the investigator the autonomy to hone in on pertinent information that may come up during the interview and thus enhance understanding (Adeoye-Olatunde & Olenik, 2021). Therefore, it was seen to be most fitting for this thesis.

The interviews were conducted with two groups of participants. The first group included individuals who have experience working in the industrial sector. This was to provide insights into attitudes towards the integration of AI within companies, what considerations are important for decision making based on the same and whether there is a comprehensive understanding of the implications of said decisions. The sample aimed to be diverse and representative by involving participants from various departments such as design, sourcing, sustainability, servicing etc. The second group included individuals who specialize in integrating AI into business operations, products and services from both within and outside the industrial

sector. The purpose of these interviews was to understand the industrial climate within which AI is or is not being integrated, how the workforce perceives AI, what opportunities have been identified, potential shifts in business models to integrate AI etc.

The interviewees were contacted via email and LinkedIn. The initial list of interviewees contacted was based on a set of potential profiles (See Table 4). Subsequently, interviewees were involved in snowball sampling, wherein they were asked to refer anyone they felt might be suitable to be interviewed for this research once they had finished their interview. They were first sent a briefing document that outlined the details and key themes to be covered in the interview, followed by a consent form to record, transcribe and publish anonymized observations. For this study, 11 interviews were conducted (See Table 5) and encompassed five countries—the United States, the United Kingdom, Sweden, Denmark and India. The average interview duration was 45 minutes and took place via online video conferencing. To maintain confidentiality, identifying characteristics of the interviewees, such as name and organization, were not disclosed.

Table 4. Initial Interviewee Profile Search

Group	Role/Expertise
Group 1 (Industrial Sector Professionals)	Design Engineers
	Sourcing and Procurement Managers
	Sustainability Managers
	Service and Maintenance Experts
Group 2 (AI Integration Experts)	AI Engineers
	Digital Transformation Consultants
	AI Ethics and Governance Specialists
	AI Sustainability Subject Experts

Table 5. Final Interviewee List

Group	Pseudonym	Role/Expertise
Group 1 (industrial employees)	Interviewee 1	Sustainability Manager
	Interviewee 2	Circularity Manager
	Interviewee 3	Design Engineer
	Interviewee 4	Innovation Engineer
	Interviewee 5	Sustainable Product Design Expert
	Interviewee 6	Product Owner and Engineer
Group 2 (AI experts)	Interviewee 7	AI Engineer
	Interviewee 8	AI Sustainability Subject Expert
	Interviewee 9	AI Sustainability and Development Expert
	Interviewee 10	Automation Software CEO
	Interviewee 11	AI Technology and Geopolitical Expert

3.3 Data Analysis

3.3.1 Thematic Analysis

Qualitative research generally employs content analysis or thematic analysis as part of its design. This research deemed thematic analysis as most appropriate. This study followed the general theme development process outlined by Vaismoradi and Snelgrove (2019)⁵.

This process started with initialization, wherein transcriptions were read, and specific meanings and phrases were highlighted and isolated. Reflective notes were then written where necessary. This was followed by construction, which involved the classification, comparison, labelling, definition and description of these units. The results of this process were extracted and embedded in a synthesis matrix. Themes were then critically analysed to identify patterns and gaps to establish knowledge and were finalized through the development of a review and analysis (See Table 6). To enhance the clarity and coherence of the findings, the selected themes were mapped to existing theoretical frameworks. This structured approach ensured a rigorous and transparent analysis process, aligning with the study's overarching research objectives.

Table 6. Themes Embedded in the Synthesis Matrix

Theories and Conceptual Frameworks	Foundations of Risk Assessment and Management	Risk and Sustainability Integration	Sustainable Business Models
	Historical evolution of risk concepts Types of risks Risk management vs. risk assessment Holistic risk management Decision-making and uncertainty	The intersection of risks and sustainability Strategic incorporation of sustainability risks Sustainability risk assessment principles and frameworks Motivations in sustainability risk management Organizational practices for managing sustainability risks	Definitions and key attributes Value creation in SBMs Stakeholder integration and governance Business model innovation as a tool for sustainability SBM archetypes Relationship between SBMs and AI
Current Knowledge	Industrial AI Capabilities and Enablers	AI for Sustainability	Sustainability of AI
	Functions and applications of Industrial AI Enabling technologies and predictive analytics AI infrastructure and decision-making in industry	Environmental benefits Social benefits Governance benefits Ethical benefits Other benefits AI as a tool for holistic sustainability solutions	Unintended consequences of AI deployment Systemic risks posed by AI Environmental risks Social risks Governance risks Ethical risks Other risks

⁵ Vaismoradi and Snelgrove (2019) outline a detailed process for theme development in qualitative research. This includes four phases—initialisation, construction, rectification and finalisation—which are further divided into stages.

3.3.2 Risk Assessment

A risk-based decision framework generally consists of three steps: (1) problem formulation and scoping, (2) planning and execution of the risk assessment and (3) risk management. Risk assessment is largely about defining a risk and its nature, its effects and likelihood. Typically, the goal of a risk assessment is to identify and explicate the risks associated with a particular action, and to examine the potential impacts of it. This was suitable for informing the answers to RQ1 and RQ2, and hence, the risk assessment was selected as a key method for this study. There are two types of risk assessments: qualitative and quantitative (and sometimes a combination of both). Qualitative risk assessments are useful in policymaking, priority setting and resource allocation, especially when there is a lack of quantitative data (Coleman & Marks, 1999). Because this study gives a high importance to findings based on perceptions, experiences and expertise, a qualitative approach for this risk assessment was deemed the most appropriate.

Based on the thematic analysis of content from the interviews and literature review, the six most commonly brought up risks were identified. The aim of the risk assessment was not to provide a comprehensive set of risks, but rather, to assess key risks comprehensively. These risks were ranked based on subjective judgments about two key factors: likelihood (how probable the risk is) and impact (how severe the consequences would be). This led to the development of a likelihood scale (See Table 7) and impact scale (See Table 8).

Table 7. Likelihood Scale

Risk Point	Likelihood	Description
1	Rare	May occur only in exceptional circumstances
2	Unlikely	Not expected but possible
3	Possible	Could occur sometimes
4	Likely	Will probably occur in most cases
5	Almost Certain	Expected to occur frequently

Table 8. Impact Scale

Risk Point	Impact	Description
1	Insignificant	Negligible impact
2	Minor	Minimal disruption or cost
3	Moderate	Noticeable and manageable impact
4	Major	Significant effects
5	Catastrophic	Severe consequences; possible shutdown

After the two scales were established, this allowed for the conception of a risk matrix (RM) (See Table 9). An RM helps in the assessment and prioritization of risks, based on the consideration of likelihood and impact (Lemmens et al., 2022)

Table 9. Risk Matrix (Likelihood \times Impact)

		Impact				
		1	2	3	4	5
Likelihood	5	M	M	H	H	C
	4	M	M	H	H	C
	3	L	M	M	H	H
	2	L	L	M	M	H
	1	L	L	M	M	H

Legend: L = Low; M = Medium; H = High; C = Critical

This risk-based framework provided a structured and systematic means to identify, evaluate, and prioritize the sustainability risks identified from the interviews and literature review. By integrating stakeholder perspectives and qualitative insights, the assessment ensured that the most salient and context-specific risks were foregrounded. This method was selected for its suitability in supporting a qualitative, perception-driven approach and for its ability to guide the analysis in addressing the study's research questions.

4 Findings

This chapter will present the results from the literature review and interviews in a systematic manner. This includes the identified risks in the risk assessment and SBM options that have been informed by the research methodology.

4.1 Risk Assessment

While the benefits of industrial AI are widely recognized, its unintended sustainability consequences remain underexplored—particularly within heavy industrial sectors. This risk assessment presents the key observations of the empirical investigation into the sustainability-related risks of AI integration in industrial contexts. Drawing from interviews and literature, six critical risk dimensions were identified (See Table 10). This is by no means an exhaustive list and carries potential for future exploration. The categories reflect a cross-section of sustainability concerns that could influence both the immediate implementation and long-term viability of AI systems. The analysis captures industry perceptions, levels of preparedness, and the divergence between technological optimism and practical concerns, revealing a complex landscape that demands a balanced and proactive approach to responsible AI adoption.

Table 10. Summary of Identified Risks

Risk	Description	Potential Impact	Existing Controls	Recommended Actions
Energy Consumption and Carbon Emissions	AI systems require significant energy for processing and storage, potentially increasing Scope 1–3 emissions and carbon footprint.	Regulatory penalties (e.g., CSRD, CBAM), reputational damage, infrastructure costs and strained partnerships.	Perceived energy savings through optimization; limited visibility into data center emissions.	Green AI and AIaaS; conduct LCAs before adoption, increase transparency in emissions reporting, prioritize renewable-powered AI systems.
Hardware and Electronic Waste	Frequent upgrades and physical AI infrastructure contribute to short-lifecycle e-waste and raw material extraction issues.	Environmental pollution, supply chain risks, non-compliance with circularity goals, investor scrutiny.	General waste management systems in place; some awareness of recyclability issues.	Circular AI; develop AI-specific recycling protocols, work with green vendors, conduct full-stack LCAs, and integrate take-back schemes.
Inequalities and Workforce Displacement	AI-driven automation may displace low-skilled labor and exacerbate inequality without appropriate transition planning.	Job losses, union backlash, talent acquisition challenges, reputational risk.	Some upskilling programs exist; recognition of cultural change needs.	Inclusive AI; establish inclusive re-skilling initiatives, ensure internal communication, and create policy for equitable AI benefits.

Bias and Programming	Bias in datasets or algorithms can lead to discriminatory outcomes and decision-making errors.	Legal risks, ESG reporting compromise, loss of stakeholder trust, regulatory penalties.	Emerging awareness; isolated use of bias mitigation techniques.	Ethical AI; implement algorithm audits, establish ethics committees, use explainable AI, and monitor models continuously.
Privacy and Cybersecurity	AI systems process sensitive data, increasing risks of breaches, misuse, and non-compliance with data protection laws.	Data leaks, production shutdowns, loss of trust, GDPR non-compliance, safety hazards.	Acknowledgment of issue; minimal dedicated strategies in place.	Privacy-First AI; Apply privacy-by-design, conduct AI-specific audits, upgrade legacy infrastructure, and align with data governance norms.
Regulatory Developments	The fast evolution of AI outpaces legal frameworks, creating uncertainty in compliance and deployment.	Market access limitations, operational delays, reputational damage, fines.	General compliance approaches; minimal regulatory expertise internally.	Build internal AI regulatory expertise, involve legal/sustainability teams early, stay updated on global AI standards.

4.1.1 Energy Consumption and Carbon Emissions

<p>Risk definition</p> <p>The deployment and operation of industrial AI systems significantly increase the use of energy and associated carbon emissions. These can potentially undermine sustainability goals and also lead to reputational, regulatory and financial consequences.</p>

Industrial AI systems process heavy amounts of data for functions such as predictive maintenance and process optimization. It is thus not a surprise that these are scaled up and run on central cloud data hubs and edge devices, that not only take up large amounts of space, but also require significant amounts of energy to run (Zhong et al., 2024). Furthermore, if these centers are powered by traditional energy sources (which is typically the case), it also increases the carbon footprint of industries on a sectoral scale.

From a business perspective, this is pivotal, as these emissions can fall under Scope 1, 2 and 3 (Wang et al., 2024a). Scope 1 emissions increase when a company develops an in-house AI system, in which case it takes on the burden of data processing and associated consumption. Scope 2 emissions increase when a company outsources its AI-related development to a third party, wherein data centers are not owned by the company. Lastly, Scope 3 emissions increase when other partners that are upstream or downstream across the supply chain utilize AI. IEA (2025) projected an increase in data center electricity consumption of 15 percent every year, between 2024 and 2030. This surpasses the growth of electricity consumption in other sectors

fourfold. Yet, this would represent a 3 percent share in global electricity demand, meaning that this aspect remains un concerning on a global scale.

An increase in emissions, however, is a likely concern in the context of an industrial business, as they often deal with B2B transactions and acquire machinery parts from other vendors. Not only can this clash with net-zero targets, but also affect client expectations and relationships (Xu & Song, 2023). Additionally, it can affect partnership relationships built on similar values and sustainability objectives. All of these compound reputational risks, especially if there is a threat of greenwashing when a firm does not accurately represent its carbon cost. Additionally, this can add to the risk of carbon taxes or penalties under regulations such as the Corporate Sustainability Reporting Directive (CSRD) and the Carbon Border Adjustment (CBAM). Lastly, this can result in forced infrastructure upgrades (such as cooling within data centers), thereby increasing costs and resource inputs (Wang et al., 2024a).

Energy consumption and carbon emissions were a topical discussion point among interviewees, as 72.7% of them believe that these dimensions are a major sustainability concern when implementing AI solutions. It is interesting to note that 4 out of 5 interviewees in Group 2 (AI experts) believe that the impacts of AI on energy consumption and carbon emissions are overstated and exaggerated. Interviewee 8 stated that while there is valid concern in these aspects, it is not to the extent outlined in most news articles. Industrial employees (Group 1) believe that the gains coming from the use of AI for energy efficiency and decarbonization far outweigh the risks it brings in these two areas. This is supported by findings from the IEA (2025), who estimate that energy savings of 8 percent can occur in the light industrial sector, namely manufacturing and machinery.

A dominant perception of AI emerges as 5 out of 6 interviewees in Group 1 claim that AI is mainly used for optimization functions such as process efficiency. Additionally, a majority of participants feel that there is not enough data to underscore the exact impact of AI on energy consumption and carbon emissions. Interviewee 4 even stated that AI emissions do not fall under Scope 3. A lack of data was assented, as 90.9% of interviewees stated that there is limited visibility on the carbon intensity of data centers. Some interviewees suggested that before adopting AI, organizations can conduct LCAs for AI solutions. They see AI as a tool with the potential to support climate assessments and scenario modeling. Notably, they cite AI as a key solution for sustainability reporting in the future.

4.1.2 Hardware and Electronic Waste

Risk definition

The implementation of AI increases demand for electronic components and hardware upgrades, which puts pressure on resources and generates larger amounts of waste. This can have negative implications for circularity objectives and environmental impact.

The implementation of AI systems entails more than software and is heavily dependent on a complex hardware backbone. This includes sensors, servers, processors, edge devices and specialized machinery. This helps with collecting, processing and analyzing data in real time. While these various technologies enable advanced automation and optimization, they also exacerbate the consumption of electronic materials, which can often have short lifespans and are difficult to recycle. Collecting, shipping, recovering and disposing of AI-related hardware has impacts not limited to air pollution, radioactivity, acidic leakage and groundwater pollution (OECD, 2022).

Especially considering that AI systems need frequent upgradation to improve compatibility and performance, as well as keep up with evolving technologies, older hardware can very quickly become obsolete and lead to larger accumulations of waste (Wang et al., 2024b). Accelerated obsolescence will increase the need for the disposal of e-waste. As of 2022, computer infrastructure accounts for 25 percent of global electronic waste (12 million tonnes) (Sustainable Infrastructure Alliance, 2022). This not only creates environmental risks for companies, but also operational risks. Many companies do not have adequately established waste processing channels or take-back systems, which can have drastic consequences. From a business perspective, this can hinder circularity and waste management goals. The improper disposal and lack of transparency in hardware lifecycles can lead to reputational damages, regulatory penalties and supply chain scrutiny. It can also aggravate investors who give importance to sustainable procurements and LCAs.

When we zone in on supply chain risks, it is easy to understand that the sourcing of hardware-intensive AI systems is a major issue. The mining and extraction of rare earth metals required for the chips, batteries and other elements of the hardware are intertwined with pollution, biodiversity damage, ecosystem degradation, human rights violations and geopolitical tension (Soryan, 2025). As supply chains become increasingly scrutinized under regulations such as the CSRD and the European Union (EU) Ecodesign Regulation, companies will be expected to disclose the sustainability impacts of their procurement strategies.

This dimension sees less of a consensus compared to others, as only 54.5% of interviewees acknowledge the growing concern around hardware sustainability in the AI ecosystem. While many see digitalization as a pathway to sustainability, they admit that the physical footprint of AI infrastructure is often overlooked. In fact, 6 out of 7 interviewees in Group 1 expressed that their companies do not yet have clear guidelines or recycling protocols for AI-related hardware. Interviewee 11 commented that “AI is treated as software, but the hardware behind it is what creates lasting waste.” Others noted that supplier transparency regarding hardware origins and recyclability is limited, making it difficult to trace environmental impacts. Some participants emphasized the potential for circular solutions, such as leasing AI-enabled devices, participating in hardware take-back programs, or collaborating with green-certified electronics vendors. They grouped the management of waste from AI with other waste, citing that this type of waste does not need to be looked at in isolation. Rather, it was part of the bigger waste management picture. Essentially, if a company has effective waste management strategies in place already, it would not be difficult to integrate waste from AI into those channels. A few even proposed lifecycle assessments not just for the software, but for the full AI hardware stack.

4.1.3 Inequalities and Workforce Displacement

Risk definition

AI-driven automation and optimization have the potential to displace certain job roles or disproportionately affect lower-skilled workers, exacerbating inequalities and triggering resistance, reputational harm, or social sustainability concerns.

As AI becomes more and more integral to industries for tasks such as predictive maintenance, quality control and process optimization, many roles—particularly jobs that require repetitive behaviours or manual labour and are prone to human error—are at risk. Automation and AI are positioned as tools for improving productivity and operational efficiency, but its integration has the potential to create significant shifts in job roles, if not for direct job losses (D. A. S. George, 2024). These shifts and losses can disproportionately affect lower-skilled workers and

widen socioeconomic divides. Due to these factors, AI is often associated with the displacement of workers.

The manufacturing sector is estimated to account for 45 percent of the overall impact of AI adoption on employment (Bonfiglioli et al., 2024). High automation industries that engage in heavy production, such as transportation equipment and woodwork are projected to be the worst hit (See Figure 5). This risk is thus even more pronounced in industrial settings, where a large portion of the workforce may lack the technical skills or resources to adapt to AI-integrated environments. To address this obstacle, companies often seek to reskill or upskill their staff. However, this can present challenges surrounding accessibility, education level, digital literacy and more (Chen & Wang, 2024). Inadequate training and transition planning can alienate parts of the workforce, which can in turn lead to resistance to digital transformation, internal dissatisfaction or increased employee turnover. An accumulation of these issues can also result in unionized resistance. The perceived threat of AI can also play a role, which sheds light on the lack of knowledge and misinformation regarding AI. All these effects can negatively affect businesses and stakeholder relationships. There can also be difficulty in attracting skilled labor if a company is seen as overly reliant on machines at the expense of humans (Yeh et al., 2020). Companies that fail to manage a transition of this nature are at risk of reputational damage, scrutiny from socially conscious investors and non-compliance penalties that prioritise fair labour practices, such as the Global Reporting Initiative.

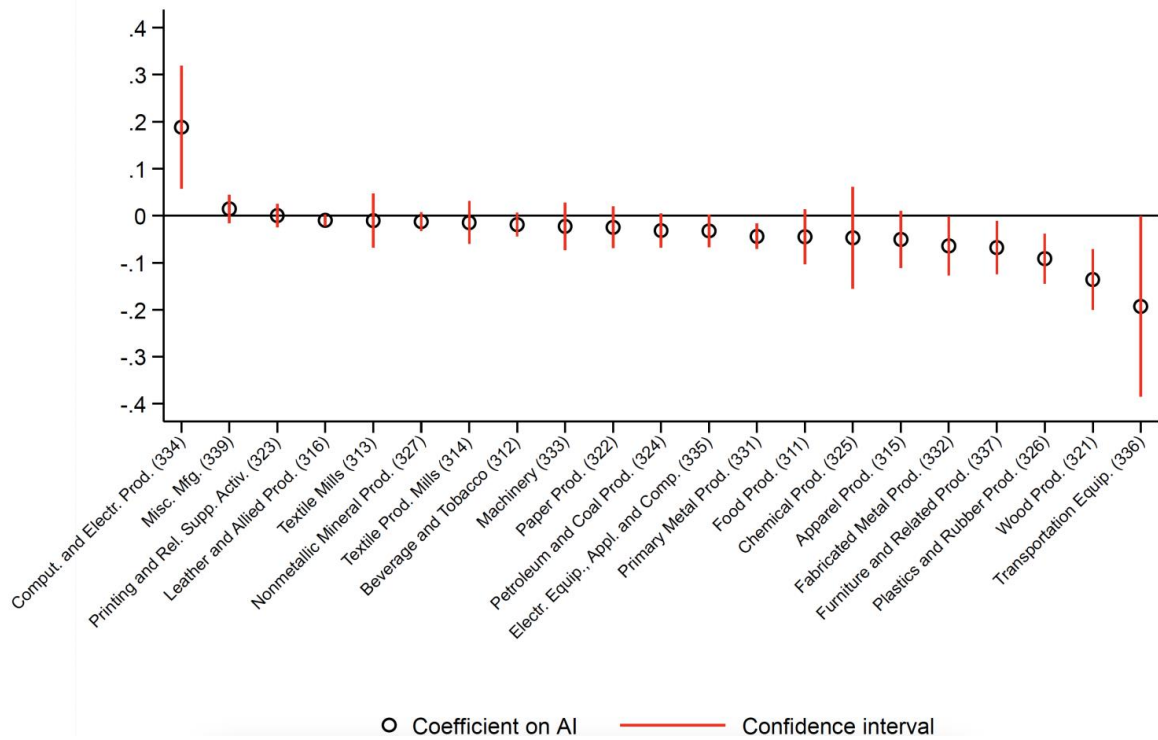


Figure 5. The Effects of AI Adoption on Employment in Individual Manufacturing Industries (Bonfiglioli et al., 2024)

Workforce displacement is perceived to be a crucial hindrance to the adoption of AI, as 72.7% of interviewees flagged workforce displacement as a long-term risk, particularly in traditional manufacturing sectors. However, perspectives varied across functions and this percentage came predominantly from Group 1. Interviewee 8 emphasizes that AI only takes over redundant jobs, and rather than replacing humans, it eases the burden on them. A common perception across groups was seen with regard to knowledge and capacity building, where every interviewee from both Group 1 and 2 emphasized that AI should be paired with robust reskilling programs and

internal communication strategies to avoid fear-based resistance. Interviewee 4 noted, “AI is not just a tech upgrade—it is a cultural shift. If you ignore the people part, you are setting yourself up for failure.” Others mentioned that while AI may eliminate some roles, it also opens opportunities in data analysis, maintenance, and system management—roles that could be filled with the right training pipeline. However, a recurring concern was the lack of clear pathways or funding for such transitions. A few interviewees also cautioned that without policies to ensure equitable access to AI benefits, marginalized groups—such as women, immigrants, or workers in developing regions—could be left behind entirely.

4.1.4 Bias and Programming

Risk definition

Bias within a program can lead to the unintentional embedding of social, operational, or cultural prejudices into AI systems, stemming from skewed training data, flawed algorithms, or insufficient governance.

Industrial AI solutions are increasingly being used for predictive maintenance, supply chain optimization, quality assurance, and even strategic decision-making. However, there is growing concern regarding the biases that these AI models can introduce into organizational processes. Bias in AI systems often originates from the historical datasets used for training, the design of the models, or even the organizational assumptions embedded into the system. In industrial contexts, this can manifest as skewed maintenance prioritizations, resource allocations, hiring decisions, or supplier evaluations—all of which can inadvertently perpetuate systemic inequalities or operational inefficiencies (Roselli et al., 2019). Left unchecked, bias risks undermining both operational integrity and corporate social responsibility objectives.

From a business perspective, biased AI decision-making can expose companies to reputational risks, legal liabilities under anti-discrimination laws, and strained client or supplier relationships, particularly in highly globalized and diverse industrial markets (Gichoya et al., 2023). Moreover, upcoming regulations such as the EU AI Act and various national frameworks are beginning to mandate transparency, fairness, and non-discrimination in algorithmic decision-making, making this risk both ethical and regulatory in nature. The identification of bias poses a challenge to approximately 83% of the machine learning workforce (Hoerl, 2024). Companies failing to address bias may face audits, fines, or demands for system overhauls, leading to unexpected costs and delays (Gichoya et al., 2023). Furthermore, as organizations increasingly integrate AI into their sustainability reporting and ESG frameworks, bias in decision-making systems could compromise the quality and credibility of reported outcomes. Biased algorithms not only replicate but often amplify underlying disparities present in training data. While some industrial leaders believe that current uses of AI (such as process control, energy management) pose minimal social bias risks, others acknowledge that as AI systems become more autonomous and strategic, the risk will escalate (Roselli et al., 2019).

There is uncertainty reflected in the interviewees’ responses to bias, where 63.6% of interviewees emphasized that bias is a major concern when scaling AI systems beyond narrow technical functions into broader operational or human resource-related areas. This was largely pushed by the interviewees in Group 2, who all recognized the dangers that come with programming that propagates bias. Interestingly, some industrial practitioners argued that bias risks are still ‘invisible’ in many contexts because the outputs of industrial AI are often complex and opaque, making bias detection difficult without specialized auditing. Four interviewees noted that bias management should be addressed proactively through algorithmic audits, ethical AI committees, and bias mitigation techniques such as balanced datasets, fairness-aware

modeling, and explainable AI tools. Furthermore, the majority believed that while bias cannot be eliminated entirely, it can be minimized to acceptable levels through continual model monitoring and third-party validation.

4.1.5 Privacy and Cybersecurity

Risk definition

The integration of AI systems into industrial operations creates new vulnerabilities for cyberattacks, data breaches, and unauthorized surveillance, jeopardizing privacy rights, intellectual property, and operational integrity.

The integration of AI into industrial systems includes the processing of large datasets, which are collected from sensors, machinery and user interfaces. This opens new fronts of vulnerabilities—namely related to data privacy and security. Data collected for AI operations can often include sensitive operational, employee and customer data. In a B2B context, it is not ideal for companies to share their data for interpretation by another company’s software. The surface area for data exposure grows substantially and thus poses a critical risk to corporate integrity and stakeholder trust.

AI systems can inadvertently or directly collect and process personal or proprietary information without explicit consent, contractual awareness or appropriate safeguards (Elliott & Soifer, 2022). This can be even more difficult to account for across borders and jurisdictions. This increases vulnerability to the violation of data protection regulations, such as the General Data Protection Regulation. Furthermore, AI technologies can be exploited via data poisoning, adversarial attacks, or manipulation—posing risks to industrial safety and continuity. AI systems are more commonly targeted in cyberattacks, specifically due to their pivotal role in operations (Elliott & Soifer, 2022). A compromised system can lead to manipulated outputs, decision errors and even shutdowns in production. These pose safety and reputational threats.

This compounds with the issue that many industrial companies use legacy infrastructure that may not be compatible with the modern security protocols needed to secure AI systems. Operational downtimes can be costly in the manufacturing industry, turning a technical issue into a material issue. Additionally, the increased use of third-party platforms and cloud-based AI services has led to limited visibility into data handling, given that companies no longer have direct control (Oseni et al., 2021). AI-based monitoring tools for functions such as safety and productivity can also infringe on worker privacy and autonomy, leading to erosion of trust with upper management (Curzon et al., 2021).

This dimension is the only one to offer complete consensus, as 100% of interviewees acknowledged privacy and cybersecurity as one of the most significant non-environmental risks in AI adoption. Thus, this risk is also the most identified risk among interviewees. Several expressed concern about data sovereignty, especially when using international cloud providers. 5 out of 6 interviewees in Group 1 emphasized the lack of AI-specific cybersecurity strategies within their organizations. Interviewee 9 noted, “AI systems are built to learn and adapt. That is a double-edged sword—because they can also learn from corrupted or adversarial data if safeguards are not in place.” Other interviewees in Group 2 highlighted the risk of ‘function creep,’ where data collected for operational efficiency ends up being used for unrelated purposes without proper stakeholder awareness. A few participants pointed out that the fast pace of AI deployment often outstrips internal policy development, leaving privacy impact assessments and ethical reviews as afterthoughts. Most interviewees advocated for privacy-by-design and AI-specific security audits as standard practice. There were conflicting opinions on the use of a

‘black box’. Interviewee 6 stated that once the trust of an end-user is gained, that is when black box solutions can be implemented. On the contrary, Interviewee 8 suggested that black box technologies do not offer enough accountability for when there is a mistake in the program. Meanwhile, a minority of interviewees expressed optimism that AI could eventually strengthen cybersecurity—through anomaly detection and automated threat response—but agreed that the current landscape lacks adequate safeguards.

4.1.6 Regulatory Developments

Risk definition

The rapid shifts in AI-related legislation, data governance, and sustainability disclosure requirements introduce uncertainty, increase compliance burdens, and expose companies to legal or financial penalties.

By nature, the development and progress of AI are sporadic and rapid. Thus, this makes the integration of AI in industrial settings dynamic in a way that it is continuously outpacing the formulation and comprehensiveness of regulatory frameworks. While legislative bodies work to catch up to this phenomenon, the evolving nature of these regulations presents a significant risk for companies already deploying or planning on deploying AI technologies and systems.

The uncertainty surrounding compliance, reporting and ethical guidelines and requirements can create a volatile environment for investment, operations and strategic planning. For example, AI regulations are currently fragmented across regions and have varying degrees of stringency (Smuha, 2021). On one hand, the EU AI act aims to classify and govern AI applications based on risk levels, potentially placing industrial AI systems under “high-risk” categories—requiring companies to implement strict transparency, documentation, and risk mitigation measures. Similarly, the CSRD expands mandatory disclosure requirements, some of which may apply to AI’s environmental and social impacts. Meanwhile, sector-specific laws and standards (such as ISOs and IECs on AI governance) are gaining traction, pushing companies toward more rigorous validation of AI tools and their outcomes (Smuha, 2021).

The regulatory landscape does not just affect internal compliance. It also influences market access, stakeholder trust and innovation cycles. A company that is risk-averse and restricts the use of AI presents two scenarios—they do not deal with the negative consequences of AI and hence ‘brave the storm’ of the uncertain environment, or they lose out on innovative opportunities and fall behind in the competitive market. This poses a dilemma to industrial firms and requires a delicate balancing act for how much AI is okay. Companies that are unprepared may face delayed product launches, contract losses or non-compliance penalties. Moreover, the failure to align with emerging standards revolving bias mitigation, explainability and accountability, data governance and even environmental and social impact—can result in reputational damage and reduce competitiveness in the market moving forward.

Regulatory uncertainties are another dominant narrative in these interviews, as 81.8% of interviewees expressed concern about the pace and ambiguity of AI-related regulation. Interestingly, 9 out of 11 interviewees pointed to the lack of internal regulatory expertise on AI, emphasizing that sustainability and legal teams are often not involved early enough in AI implementation projects. Interviewee 1 remarked, “Employees often feel that they are flying the airplane while building the manual for how to land it.” Interviewee 7 referred to AI regulation as a grey area, wherein companies operate both with positive and negative flexibility. Others noted that while AI offers clear operational benefits, its governance remains poorly understood at the executive level. Some participants expressed frustration at the complexity of overlapping

frameworks—particularly for companies operating across borders. A few also highlighted the risk of overregulation, where unclear or overly stringent rules could stifle innovation and deter experimentation. However, the major opinion by 81.8% of interviewees was that regulatory developments will not impede the adoption of AI. Some interviewees welcomed regulation as a tool to level the playing field, promote responsible AI practices, and encourage long-term thinking. They suggested that proactive companies can turn regulatory readiness into a competitive advantage by embedding AI ethics and compliance into their digital strategies from the outset.

4.1.7 Other considerations

Beyond the identified sustainability risks, several considerations emerged from the literature and interviews that shape the feasibility, scalability, and long-term success of sustainable AI integration in industrial contexts. These considerations—though not always categorized as risks—act as critical enablers or barriers to sustainable AI deployment.

Every interviewee emphasized the pivotal role of internal knowledge and institutional capacity in the successful implementation of industrial AI systems. Interviewee 7 specifically mentioned that AI is now a ‘buzz word’ and many companies are eager to implement AI solutions upon encounter without a thorough feasibility analysis. While the technical functions of AI are often outsourced or integrated via third-party platforms, companies still require robust internal competencies to evaluate, monitor, and govern AI-driven processes. Interviewees frequently cited skill gaps among existing employees, particularly in interpreting AI outputs, managing data pipelines, and understanding model limitations. Notably, reskilling initiatives remain underdeveloped or underfunded and several participants also warned that overreliance on external vendors can lead to ‘tech dependency,’ eroding internal decision-making autonomy.

AI adoption is often perceived as a cost-saving mechanism in the long term, but most interviewees pointed out that initial investments are substantial. These include costs for infrastructure upgrades, hardware acquisition, integration with legacy systems, staff training, and cybersecurity. There is also the challenge of attributing sustainability-related costs and benefits directly to AI, as environmental and social impacts are harder to quantify. Additionally, ESG-focused investments in green data centers or ethical sourcing often compete with operational efficiency goals, which some participants found to be a source of internal conflict.

Several interviewees commented on the difficulty of exploring and prototyping AI use cases without sufficient data maturity. Many industrial companies lack streamlined, high-quality datasets or centralized data infrastructures, making AI experimentation costly and unreliable. Explorability—the ability to test, iterate, and pilot AI solutions before full-scale rollout—is limited by data silos, inconsistent formats, and outdated systems. Furthermore, some interviewees expressed hesitation to engage in exploratory AI projects due to the risk of operational disruptions or compliance violations.

Another prevalent theme was the tension between customized AI solutions and existing industrial infrastructure. Off-the-shelf AI tools are often designed for general-purpose applications and may not account for the nuances of specific industrial environments. As a result, companies either must invest heavily in customization or adapt their operations to suit the tool—both of which carry high resource burdens. This aligns with concerns noted in earlier sections about increased e-waste and retrofitting requirements. Companies lacking modular or interoperable systems are particularly disadvantaged, as they face higher transition costs and integration challenges.

Several participants acknowledged that supply chain sustainability and resilience are becoming increasingly relevant under the CSRD and other due diligence directives. The lack of traceability surrounding AI as a technological solution not only affects sustainability reporting but also increases exposure to geopolitical risks, market volatility, and regulatory scrutiny. Furthermore, as AI becomes a larger part of manufacturing ecosystems, companies must ensure that their suppliers meet ethical and environmental benchmarks not just for raw materials but also for software integration and data handling.

4.2 Sustainable Business Model Pathways

4.2.1 Value Pillars

Through the interviews conducted with professionals across Group 1 and 2, as well as the comprehensive literature review, several cross-cutting themes emerged as foundational pillars for enabling and scaling SBM pathways to foster the sustainable integration of AI. Following these themes may not only support the transition toward sustainability but also provide practical direction for the implementation of AI in industrial systems.

Transparency

Transparency is often perceived as a critical enabler of trust and accountability. Not only does it help with building customer relations and trust, it also promotes introspection for a company to understand the strengths and weaknesses of its progress. This involves openness and strong communication regarding changes in operations, sourcing and product/service detailing. Periodic sustainability and ethics reports and disclosures, especially when aligned with recognized standards such as the GRI, SASB, or CSRD, is an essential practice in legitimizing sustainability claims and mitigating risks of greenwashing. Transparency must ideally go beyond marketing narratives to include data-driven disclosures on sustainability performance. Here, data plays a pivotal role, as the way this data is gathered and analysed also influences the final findings. This includes openly sharing challenges and setbacks, not just successes, to foster continuous improvement and stakeholder confidence.

Stakeholder Engagement

Mapping and identifying the relevant actors in any decision often dictate its success. This is no different in the case of AI. There is a dire need for deep and inclusive stakeholder engagement. Rather than designing AI or digital solutions in isolation, there is increased value in co-creating these technologies with the communities and individuals most affected by them. This approach not only enhances the social relevance and legitimacy of innovations but also helps identify context-specific risks and opportunities early on. Additionally, it allows for companies to mitigate risk-related costs early and pre-emptively fine-tune their offerings. Effective engagement includes iterative feedback loops, participatory design methods, and ongoing dialogue across stakeholder groups—from customers and employees to regulators and marginalized voices.

Modularity

Modularity refers to the extent to which an apparatus can be broken down into independent units, often interconnected and replaceable. These units can be combined to form other wholes, thereby offering flexibility and maintainability. Increased modularity in service or product design is often cited as a practical and scalable strategy for companies at various stages of sustainability integration. Rather than requiring wholesale system overhauls, modular solutions—offered as small, stackable packages—allow clients to address discrete sustainability challenges in a manageable and flexible manner. This can be particularly valuable in contexts with limited

resources or organizational readiness. Modularity enables a phased approach to transformation, encourages experimentation, and reduces the barriers to entry for sustainable innovation.

Partnerships

Partnerships and increased collaboration can be a key mechanism to enhance credibility, broaden impact and accelerate learning. There is great strategic value in collaborating with organizations such as NGOs, academic institutions and governmental bodies. Not only can there be a pooling of resources, but also access to cutting-edge knowledge and validation/alignment of practices. Partnerships also serve as accountability structures, where external actors can help assess and strengthen a company's sustainability claims. These collaborations often act as catalysts, enabling organizations to scale their sustainable business models more effectively and inclusively.

4.2.2 Strategies

Upon the identification of the key risks posed by AI, the research was continued with the synthesis of strategies to address one or more of said risks. While these do not serve as universal solutions to all of these challenges, they may serve as a starting point when developing SBM pathways to responsibly integrate AI.

Green AI and AI-as-a-Service (AIaaS)

AIaaS is a business model that provisions AI-based services and solutions through a cloud computing platform. This is by no means a novel technology and has become increasingly popular in companies such as Microsoft. This business model pathway can serve to address the substantial energy consumption and associated carbon emissions resulting from training and operating artificial intelligence models. This is also largely supported by the interviewees, where 81.8% of respondents noted that clients (both end-users and B2B) are increasingly demanding low-carbon digital services, which could position AIaaS as a strategic differentiator.

Companies that choose to pursue this pathway would be able to optimize their AI models for energy efficiency. This would favor smaller and more performant models over large and resource-intensive ones. Advances in model compression (reducing the size of a unit while maintaining performance), making machines more computationally efficient and energy-aware parameters while running enable significantly lower energy footprints without sacrificing performance (Patterson et al., 2022). Furthermore, pushing for partnerships with carbon-neutral or green-certified data centers would reduce Scope 2 and 3 emissions linked to AI operations.

This would help in fostering a culture of transparency—one of the identified key pillars in this study. Companies would have the opportunity to create a platform that provides detailed LCAs of their AI models and clearly communicate the carbon emissions are each stage. This would push companies to better their carbon reduction strategies while also garnering a competitive edge. Interviewee 11, in fact, noted that if transparency were to become a purchasing criterion, greenwashed AI systems would not survive. If this were to also be combined with a concept such as a 'Green AI' label or certification, this could foster brand differentiation and building consumer trust. The certification could potentially include efficiency thresholds, renewable energy sources and emissions disclosures.

The macrolevel of these visions would include monetization models that would center around premium pricing for low-carbon AI offerings. Early adopters, particularly those with Science-Based Targets initiative (SBTi) commitments, could be key customers. Bundling 'Green AI' services with carbon offset packages or sustainability reporting support could create additional revenue streams. Over time, as regulatory frameworks tighten (such as the EU Green Claims

Directive), offering green-certified AI services may move from a premium offering to a compliance necessity.

Thus, by embedding sustainability into the core value proposition, the Green AI along with AIaaS model enables companies not only to reduce environmental impacts but also to gain a competitive advantage in an increasingly climate-conscious market.

Circular AI Hardware Management

To address the challenges of increased e-waste generation, in this pathway, companies develop a closed-loop system for AI hardware assets. Upon lease expiration from AIaaS or from takeback system establishment, hardware would be collected, refurbished, and either redeployed or resold at lower tiers (such as from cloud providers to educational institutions or startups). Hardware beyond repair would enter certified recycling streams, recovering precious materials while minimizing environmental leakage.

This strategy would address the often-overlooked environmental impact of AI hardware production and disposal, as revealed in the interviews. This model would successfully mirror successful examples from other sectors, such as Fairphone's modular smartphones and Cisco's circular economy initiatives (Cisco, 2020). Interviewee 11 noted that companies are willing to pay for reliability and easy upgrades, especially if circular models offer total lifecycle support and carbon savings. Incentives such as loyalty points, service discounts, or sustainability certifications for participating customers could enhance adoption. Furthermore, by embedding circularity into procurement policies, especially for public sector contracts increasingly tied to green criteria, companies can secure preferential access to major markets.

Revenue generation would thus shift from one-off sales to recurring subscription fees, refurbishment services, and second-life hardware marketplaces. The model would also improve material security and thereby insulate firms from supply chain shocks, which 92% of interviewees identified as a growing risk, especially with geopolitical tensions around critical minerals. Ultimately, Circular AI Hardware Management would operationalize the circular economy principles within AI infrastructure, creating environmental, economic, and strategic value across the hardware lifecycle.

Inclusive AI Upskilling Platforms

Inclusive AI upskilling platforms can respond to concerns about workforce displacement caused by AI automation. The research by D. A. S. George (2024) and reinforced notions by 72.7% of interviewees stress that AI adoption risks disproportionately impacting marginalized and low-skilled workers, exacerbating societal inequalities.

This business model involves offering companies a multi-objective service: conducting AI impact assessments to identify potential job displacement risks and designing tailored reskilling programs to mitigate these effects. Impact assessments would involve evaluating AI deployment projects for labor displacement probabilities across demographics, job types, and regions—modeled after established social impact assessment methodologies (Esteves et al., 2012). Training modules could focus on AI-proof skills such as creative problem-solving, interpersonal communication, and AI system maintenance, ensuring that displaced workers are redeployed rather than excluded. Upskilling platforms would partner with community colleges, NGOs, and industry associations to maximize outreach, inclusivity, and credential recognition. Training could also be offered in multiple formats—gamification, videos, text chapters etc.

Two interviewees shared similar sentiments that companies who proof their workforce for the future not only retain talent but also significantly improve their brand equity in an era of

responsible innovation. Subscription-based pricing, offering continual access to evolving skill curricula, would ensure stable revenue while aligning with client needs for ongoing transformation readiness. An important emphasis would be placed on equity: reskilling programs should be tailored to appropriately include marginalized communities and low-income workers, often overlooked by traditional corporate training initiatives. Public co-funding opportunities could also subsidize program costs, making it financially viable for a broad range of businesses. Thus, this would not only mitigate ethical and reputational risks but also strengthen business resilience, societal trust, and regulatory goodwill.

Ethical AI Certification Services

Bias in AI algorithms is a well-documented risk that can cause significant harm and reputational damage. All interview participants agreed that addressing AI bias is crucial. This strategy of fostering the certification of ethical AI would offer third-party auditing of AI models for biases across race, gender, socio-economic status, and more. Firms would develop frameworks based on existing standards such as the IEEE 7000 series and ISO/IEC 24028 guidelines for trustworthiness in AI. Certification would be earned through rigorous audits and testing, providing companies with verifiable ethical AI badges akin to Fairtrade certifications in consumer products. Additionally, companies could provide an in-house open-access ethical AI toolkit, allowing employees to conduct preliminary self-assessments of their newly developed models. This modularity would allow entry points for projects of varying sizes and maturity levels. Building a strong brand around independent, rigorous certification could also enable cross-sector partnerships with insurance providers (for bias liability coverage) and public institutions. In sum, Ethical AI Certification Services would translate the abstract ethical imperative into a concrete, actionable, and monetizable business service that promotes fairness while reducing risk.

Privacy-First AI Solutions

Privacy preservation was a universal concern among interviewees and thus requires a strategy to protect consumers. The 'Privacy-First' business strategy can respond to intensifying concerns around personal data security, particularly with AI models reliant on vast, sensitive datasets. An innovative feature would be offering privacy insurance packages—providing clients with financial protection against damages caused by AI-related data breaches. The dual proposition entails technical excellence alongside insurance coverage, which would meet both technical and risk management needs, appealing strongly to companies within the industrial sector. Revenue streams would include project fees, SaaS subscriptions for privacy-first model development environments, and premiums from privacy insurance partnerships.

Companies operating under this model would specialize in privacy-preserving technologies such as federated learning, differential privacy, and homomorphic encryption (Shokri & Shmatikov, 2015). These techniques allow AI models to learn from decentralized data without directly accessing personal information, significantly reducing breach risks. Interviewee 3 noted that privacy is not just about compliance, but also about defining brand value in the context of AI. Thus, firms would position themselves as industry leaders of data sovereignty, offering AI services that guarantee user control, consent, and transparency. Thus, Privacy-First AI Solutions can create a competitive moat by turning privacy from a compliance burden into a strategic asset, building resilience and trust in AI ecosystems.

5 Discussion

This section critically interprets the findings presented in the previous chapter. By analyzing the implications of the results, it offers reflections on the significance of these observations in the context of the industrial sector and its integration of AI in a sustainable manner.

5.1 Decision Context

An understanding of the situation and objectives surrounding the risk assessment process is crucial, especially when succeeding it with a decision-making process. Decision context refers to strategic decision characteristics, specific to the situation influenced by the external environment and firm characteristics (Shepherd & Rudd, 2014). Not accounting for these variables can lead to an incomplete and/or inaccurate picture for decision-making. The decision context encompasses why risks are perceived, assessed and ultimately addressed in a particular manner.

In this study, the risk assessment is shaped by the evolving realities that industrial companies face—namely, those operating in manufacturing and B2B firms. The characteristics of these firms typically include long-standing partnerships, capital-intensive products, the prioritization of operational efficiency, process innovation and long sales cycles. These features may have particularly influenced perceptions about workforce displacement, regulatory developments and privacy and security. The organizations represented in this research can be generalized as industry leaders with established sustainability goals and active commitments to advancing these within their operations and value chains. They have positioned themselves at the forefront of corporate sustainability efforts and have set ambitious targets to integrate sustainability into strategic decision-making. Thus, sustainability concerns are not neglected in interviewees' considerations and may have affected their perceptions of energy consumption, carbon emissions and e-waste.

Zooming out onto the external context gives us a more complex setting. Legislative developments such as the CSRD, the Omnibus Directive, and other upcoming regulations like the Corporate Sustainability Due Diligence Directive (CSDDD) are elevating the expectations surrounding transparency, accountability and risk management. These frameworks serve as a critical basis for the perceptions of the industrial workforce, and this reflects on the broader regulatory pressures influencing industrial priorities. Many of the industrial companies reflected in this study are already implementing AI solutions, primarily to optimize processes, increase resource efficiency, and enhance operational performance. However, the legislative environment surrounding AI remains uncertain, especially regarding future rules on data governance, ethical use, and accountability. In many cases, companies' perceptions of AI-related risks are still emerging or incomplete, shaped by their immediate operational experiences rather than a comprehensive understanding of the broader implications.

To address this gap and complement the industry-focused perspectives, the study also included insights from specialists working at the intersection of AI and sustainability. These experts bring a deep technical understanding of AI systems, including experience in coding machine learning algorithms and developing cutting-edge solutions specifically tailored for industrial applications. Their involvement provided a more fundamental view of the opportunities and risks inherent in AI deployment, particularly from the design and implementation phases onward. However, these professionals are not necessarily tied to the same sustainability obligations as the former group. Hence, their perspectives were more focused on aspects such as privacy and security, bias and programming etc. By combining this technical insight with industry-based perspectives, the assessment was able to capture a more holistic view of how AI is influencing sustainability strategies and risk perceptions within industrial sectors.

In addition, preliminary discussions within companies about transitioning to sustainable business models—such as circular economy approaches, servitization, and regenerative value creation—highlight strategic risks tied to long-term business transformation. While these ideas are gaining traction, they remain in early stages for many organizations, introducing new uncertainties regarding customer adaptation, operational change, and strategic realignment. Given these factors, the interviewees’ responses were influenced by both immediate operational challenges and the broader, more uncertain future landscape shaped by regulatory shifts and technological innovation. Additionally, the interviewees from Group 1 did not have the foundational knowledge to meaningfully contribute their opinions on SBMs relevant to this study. This could largely be due to the current scale of deployment of AI, where companies have not yet critically examined the need to shift to more sustainable models of operation because of the effects of AI. The narratives surrounding the SBMs were largely based on responses from Group 2, as well as support from the literature.

Overall, the context framing this sustainability risk assessment reflects a dynamic intersection of compliance demands, technological disruption, and strategic transformation. Understanding the findings requires recognizing that industrial companies and AI specialists alike are navigating a rapidly evolving environment, where sustainability, innovation, and regulation are increasingly interconnected. These contextual layers help explain why certain risks stood out during the assessment while others remained more muted or speculative. Rather than viewing the results in isolation, they are best understood as reflections of an industrial sector in transition. This dynamic environment forms the backdrop against which risk perceptions are constructed and assessed.

5.2 Risk Matrix

Having explored the broader context in which industrial companies perceive and assess sustainability risks related to AI, the next section operationalizes these insights through a structured risk matrix. This matrix tabulates the severity of the identified risks by likelihood and impact (See Table 11). It is followed by a visualization of the results (See Figure 6). It is informed by the findings of this study and can help decision-makers in the industrial sector identify which risks require immediate attention, mitigation strategies, or monitoring. This can be especially valuable in sustainability contexts where complex, multidimensional risks must be managed systematically.

Table 11. Qualitative Ranking of Risks

Risk	Likelihood	Impact	Level
Energy Consumption and Carbon Emissions	4	4	H
Hardware and Electronic Waste	3	3	M
Inequalities and Workforce Displacement	5	4	H
Bias and Programming	4	2	M

Privacy and Cybersecurity	5	5	C
Regulatory Developments	5	2	M

Legend: L = Low; M = Medium; H = High; C = Critical

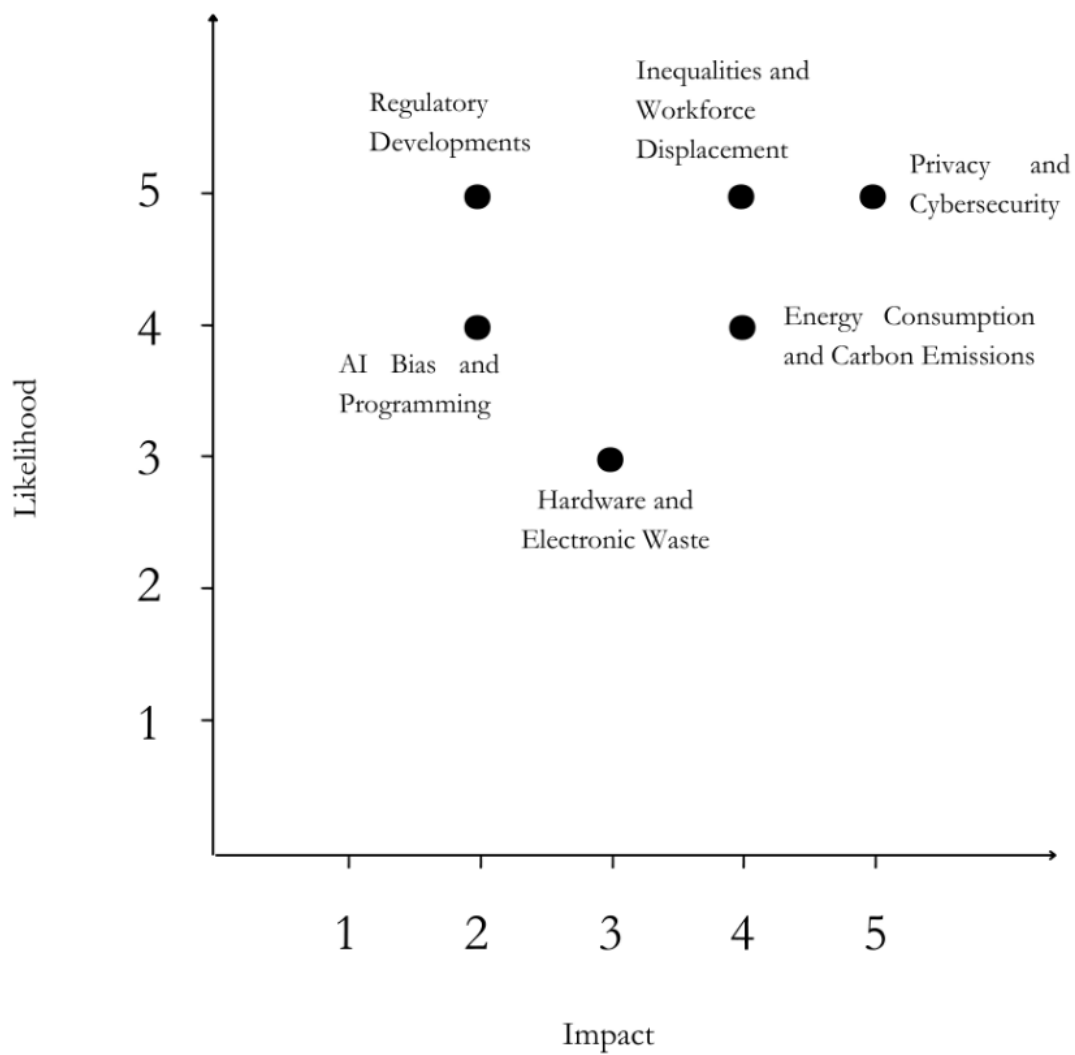


Figure 6. Visualization of the Risk Matrix

Privacy and cybersecurity are ranked as the most critical risks, garnering a need for urgent action from both interviewees and literature. In the context of the industrial sector, this is also the area that is most concerning to customers, as B2B companies are afraid of information leakage through technologies such as sensors which can read details such as production units, runtimes, downtimes etc. Additionally, the vulnerability of production areas to cyberattacks poses a huge obstacle for companies looking to scale the use of AI into their product offerings and services.

Inequalities and workforce displacement are intertwined with any discussion surrounding the integration of AI. The notion that AI replaces humans and can work better and more efficiently places pressure on the workforce. There is thus resistance to the internal development of AI within a firm, leaving employees to lose trust with upper management and also repelling other potential talents from joining the organization.

Energy consumption and carbon emissions will inevitably rise with the use of AI. This presents an environmental risk to companies that are actively working to curb carbon emissions and energy consumption through their sustainability goals. Yet, it does not surpass the two highest ranked risks, as AI has the potential to counter some of these effects through its optimization and efficiency functions that can also work towards decarbonization. This, however, is largely based on data availability and comprehensiveness, which is uncertain.

Regulatory uncertainties ranked as the fourth most likely risk, given that the likelihood of these uncertainties existing is essentially guaranteed. Given the sporadic nature of development of AI, it is risky for companies to invest in state-of-the-art infrastructure, tailor operations and re-skill labourers, only to revamp to comply with emerging regulation conscriptions. Nonetheless, it is not perceived as high risk, as this is not a defining reason that hinders companies from implementing AI integration procedures.

Hardware and e-waste and programming bias are closely ranked together and round out the risk matrix. While they present valid concerns, with the latter specifically exhibiting high likelihood, they are not seen as very urgent. Hardware and e-waste may present problems that can be solved using takeback initiatives and efficient retrofitting methods. While programming bias is bound to occur in the development of an AI model, its effects are often difficult to trace and challenging to mitigate absolutely. Because of this, it is important for companies to obtain more knowledge, but it does not come as an immediate concern.

While the risk matrix offers a high-level prioritization of sustainability risks, a deeper exploration is necessary to understand the nuances behind the risks and overall findings. The following analysis interprets these rankings by drawing on stakeholder narratives and academic literature to uncover systemic patterns and emerging tensions.

5.3 Interpretation of Results

The findings reveal tensions between leveraging AI for operational efficiency and managing its associated sustainability risks. This tension manifests across all identified risk categories, from energy consumption to workforce displacement.

The literature gap highlighted by Peres et al. (2020) was vital, as the responses from interviewees reflected that the industrial sector lacks a comprehensive framework and roadmap for integrating AI into business models and operations. It was thus important to apply a stakeholder-informed perspective to the sustainability risk assessment. The respondents from Group 1 revealed how industrial actors currently understand and respond to AI-related sustainability risks, if at all. On the other hand, the respondents from Group 2 surfaced the emerging narratives, practical barriers, and organizational blind spots that hinder strategic

integration from a sustainability perspective. Furthermore, the proposed SBM pathways serve as foundational components for building a more coherent and actionable roadmap for AI adoption.

Among environmental risks, energy and emissions seemed to garner the most observations from both groups. Interestingly, the literature surrounding energy consumption and carbon emissions offers a consensus: the increased use of AI results in increased energy usage and carbon emissions. This was also agreed upon by the interviewees in Group 1. Yet, the interviewees in Group 2 voiced that many of the numbers provided by literature sources can be inflated. They recognized that while AI may have an impact on these dimensions, they are nowhere near the quantification offered in current reports. It may be the case that interviewees in Group 1 were susceptible to information from news articles rather than their own experiences or knowledge. Many of them admitted to having incomplete knowledge on the subject, which could coincide with the sudden spike in published articles on AI and energy/emissions in 2024. This phenomenon may not be restricted to these dimensions and could have affected interviewees' answers across other AI-related risk subjects as well.

Compared to energy and emissions, hardware and e-waste-related risks were comparatively lower on the list of concerns for interviewees. Once again, the literature is clear that the use of AI increases e-waste, which can in turn lend itself to ineffective management of waste. However, both groups of interviewees were clear that this risk was not as much of a concern because in most industrial companies that position themselves as industry leaders, waste management systems are already in place. The effort should be more pertinently focused on formulating guidelines for e-waste that extend to AI. Though half of the interviewed population did not express legitimate concern in this dimension, it was consistent across the board that they were willing to admit that this might be due to a lack of knowledge.

These patterns reveal an unease with the rapid integration of AI technologies in the absence of analogous sustainability guidelines. Organizational readiness to adopt AI appears to be driven more by technological enthusiasm than by a clear understanding of long-term impacts. This reflects the need to move beyond reactive compliance toward proactive, context-sensitive approaches that ensure digital innovation aligns with sustainability goals. These issues reflect a broader disconnect between the progress of digital innovation and sustainability ambition. While both are often championed as top priorities within organizations, they are typically pursued in parallel rather than in alignment. Not only does this increase vulnerabilities to risks, but it also overlooks synergies between the two progress paths. This underscores the need for systemic AI governance approaches that embed long-term sustainability considerations and stakeholder inclusion into the design and implementation of AI strategies.

Data availability was a recurring theme across 100% of the interviews. Every participant brought up the availability and quality of data while discussing the potential of AI, underscoring that if the data is easily available, they would be more willing to integrate AI into their business practices. This, however, shifts the onus of innovation away from the company. While firms want to market AI as a unique selling proposition, they also do not want the first movers' advantage on the technology. This is largely because of the time and effort that can be saved by waiting for another company to break into untapped potential. At the same time, data availability was used as a metaphorical crutch to explain why any negative effects of AI were unknown to the company. This is, however, contradictory to other observations made by the set of interviewees in Group 1, who were articulate about the many risks that come with implementing AI from a sustainability perspective.

Knowledge gaps⁶ and misinformation also seemed to be a key theme across the interviewees and the literature. This can especially be seen with the lack of clarity on the relationship between AI and scope 1, 2 and 3 emissions. It can also be seen with dimensions of privacy and cybersecurity, where interviewees point to an increased adoption of AI without a holistic understanding of it. However, it is the case that many of the key concerns surrounding AI can easily be attributed to other digital technologies that have existed for many years. As such, many of these concerns are not new and hence would foster a particular baseline of understanding within the workforce. Thus, there does seem to be a lack of accountability while adopting AI, with an attitude that companies cannot be held liable if they do not know about the negative effects. This raises the larger question of whether technology should be deployed at all without sufficient knowledge of its risks and effects.

This also reinforces the assertion presented by Zio (2018) that risk assessment outcomes must not only be technically robust but also presented in a form that is interpretable and actionable for decision-makers, who often operate under conditions of ambiguity. The lack of traceable, context-specific information in the current industrial landscape appears to hinder both strategic clarity and organizational responsiveness. In this sense, sustainability risks associated with AI are not just a matter of data availability and incomplete knowledge but of knowledge translation and transparency. Ensuring that decision-makers can navigate these uncertainties requires structured frameworks that bridge technical insights with stakeholder understanding—an objective that the proposed SBM pathways attempt to address. However, the lack of robust, integrated frameworks to govern the sustainability implications of AI points to a critical gap in current practice. Many industrial firms still approach AI and sustainability as separate domains, rather than recognizing AI as a potential amplifier of existing sustainability risks or enabler of transformative opportunities. This misalignment reinforces the argument that sustainability risks posed by AI should not be examined in isolation but assessed as part of a broader sustainability strategy and governance.

Interviewees from Group 1 often offered dual perspectives, wherein they reflected on their own perceptions of the subject matter while also representing the scenarios put forward by the larger organization they belonged to. Of course, this meant that their perceptions of the potential and/or harm of AI did not align with those of their company. This only further cements the fact that the reception of AI in the workforce is largely based on perception, and often, a company's actions pertaining to AI may not reflect the best interests of all stakeholders. It is thus integral that the pillar of stakeholder engagement is upheld throughout any decision-making process related to AI. This also lends itself toward workforce resistance, as these notions display that there has not been adequate participation of employees in executive discussions for settling on the course of action to deploy AI.

The findings indicate that interviewees flagged workforce displacement as a long-term risk, particularly in traditional manufacturing sectors. However, the universal recognition across both interview groups that AI should be paired with robust reskilling programs suggests an emerging consensus on the importance of human-centered AI deployment strategies. The Inclusive AI Upskilling Platforms pathway operationalizes this consensus by creating guided approaches to workforce transitions. This aligns with the concept of just transition from sustainability literature (Stavis & Felli, 2020), which emphasizes the importance of ensuring that shifts toward more sustainable systems do not disproportionately burden vulnerable populations. By focusing on

⁶ For the sake of clarity in this discussion, there is a differentiation between the terms 'data availability' and 'knowledge gap'. The former refers to information from a technical perspective, a lack of which would possibly hinder technological advancement and innovation. The latter refers to information from a self-perception perspective, wherein this serves as an obstacle to the progress of an individual in relation to a certain system or apparatus.

equity in reskilling programs, this pathway addresses concerns about AI exacerbating existing socioeconomic divides.

It was evident that bias is a major concern when discussing scaling AI systems and highlights the growing recognition of AI's social sustainability dimensions. The divergence between Group 1 and Group 2 perspectives on this issue—with the latter more acutely aware of bias risks—suggests an awareness gap that needs addressing in industrial contexts. The Ethical AI Certification Services pathway responds to this gap by creating standardized frameworks for assessing and mitigating bias. This pathway illustrates how social sustainability considerations can be operationalized within business models, moving beyond abstract ethical principles to concrete practices and services. Because employees within the companies displayed a lack of concern in this dimension, it seems as though bias in programming AI models is inevitable. Thus, it will likely continue in practice, namely because its effects are invisible at first. Overall, the findings underscore that bias is not just a technical glitch but a systemic risk factor that requires dedicated governance mechanisms as industrial AI solutions mature.

The risk assessment revealed that regulatory developments represent a significant concern, indicating that many organizations view sustainability primarily through a compliance lens. However, the SBM pathways identified in this research suggest a shift toward viewing sustainability as a strategic imperative that can drive innovation and market differentiation. This transition from compliance to strategic advantage is particularly evident in the Ethical AI Certification Services pathway, which transforms ethical considerations from abstract compliance requirements into concrete, marketable services. Similarly, the Privacy-First AI Solutions pathway positions data protection not merely as a regulatory obligation but as a core value proposition. These approaches align with Nidumolu et al.'s (2009) assertion that sustainability can be a driver of innovation rather than merely a cost center. Relying solely on external compliance pressures is insufficient. As the findings indicate, companies must begin treating sustainability not just as a checkbox for regulation but as a strategic and ethical lens for innovation. The pathways proposed in this study aim to support this shift by operationalizing sustainability in ways that are both market-relevant and values-driven.

To address the strategic blind spots revealed in the interviews, the study introduced a set of SBM pathways that have been previously mentioned several times in this section. These pathways are not prescriptive but serve as conceptual tools to guide more responsible and future-ready AI integration strategies. For instance, the Green AI and AIaaS model demonstrates how sustainability can be embedded within innovation rather than positioned as its constraint. This aligns with Porter and Kramer's (2011) concept of creating shared value, where addressing societal challenges becomes a source of competitive advantage rather than an external cost. The findings suggest that organizations able to proactively integrate sustainability considerations into their AI governance frameworks may gain first-mover advantages in an increasingly regulated landscape.

The findings call for a revisiting of the assertion presented by van Wynsberghe (2021). The opinion largely reflected by the interviewees was that the sustainability of AI does not present a huge concern, given that AI for sustainability facilitates the gains that it shows potential for. This, of course, would be specific to each risk, as AI presents varying levels of challenges and opportunities across them. This is an interesting viewpoint, given that data availability, knowledge gaps and lack of capacity were all discussed by the same interviewee pool. Hence, the perspective that one dimension outweighs the other cannot be taken at face value. This sheds light on how both the sustainability of AI and sustainability for AI are important. The distinction is crucial, and it is essential that organizations develop the capacity and understanding of both.

The structuring of this study was found to align with the three-step protocol for sustainability perspective integration in risk management presented by Schulte & Hallstedt (2018). Firstly, sustainability effects were identified through the interview process. Internal stakeholder value was brought up in discourse surrounding (but not limited to) job satisfaction, training, and transparent governance. Furthermore, external stakeholder value was highlighted in discourse surrounding (but not limited to) collaborative ventures, transparent communication, compliance and ethical practices. The inclusion of sustainability in objective setting within organizations was discussed in these interviews as well, which particularly underscored perceptions of various sustainability risks and how they affect the decision-making surrounding the adoption of a digital technology—AI. Lastly, developing concrete support to identify and manage sustainability risks was a methodological aim of the study in itself, wherein the sustainability risk assessment led to a risk matrix and ranking of risks in an industrial context and recommendations for pathways to move forward in an ethical and responsible manner.

The sustainability implications of AI are contingent on how organizations structure their governance processes and strategic priorities. The findings demonstrate that the adoption of AI is often guided by operational or innovation-driven goals, with limited integration of long-term sustainability considerations. This reinforces the notion that technological systems do not produce sustainability outcomes in isolation; rather, such outcomes are mediated by the institutional frameworks, value orientations, and stakeholder engagement processes that shape their deployment. Consequently, sustainability risks linked to AI should not be treated as discrete or exceptional, but as interdependent with broader organizational sustainability challenges. A fixed implementation roadmap is impossible in a dynamic context. Therefore, highlighting the drivers and constraints that influence the capacity to align AI integration with sustainability ambitions—particularly within industrial environments where competing priorities frequently coexist—can be pivotal in shaping effective decision-making in an organization.

6 Conclusion

This concluding chapter addresses the two research questions that guided this thesis, articulates practical implications, offers concrete recommendations, and proposes avenues for future research.

This thesis had two general objectives: (1) identify and contextualize the sustainability risks posed by AI to the industrial sector and (2) propose SBM pathways for industrial companies in response to the identified risks. The thesis achieved this objective by exploring the sustainability risks of industrial AI systems through a qualitative, stakeholder-informed risk assessment approach. Drawing from semi-structured interviews, literature synthesis, and a sustainability risk matrix methodology, it has examined how the rapid deployment of AI technologies in manufacturing and industrial sectors intersects with sustainability considerations. The research responds to the pressing need to bridge the current knowledge gap between AI innovation and sustainable transitions by offering both critical insights and actionable pathways for business model transformation.

6.1 Revisiting the Research Questions

The thesis posed two key RQs. The findings for both RQs informed the other and allowed for a robust discussion of observations.

RQ1: How does the integration of AI as a tool pose sustainability risks for industrial companies?

The research revealed that AI in industrial contexts is a double-edged sword—capable of enabling decarbonization, efficiency, and resource optimization, but is also associated with new and underexplored sustainability risks. Six key risks were discussed in this study: energy consumption and carbon emissions, hardware and e-waste, inequalities and workforce displacement, bias and programming, privacy and cybersecurity and regulatory developments. Among the identified risks, those related to privacy and cybersecurity, workforce displacement, and energy consumption were ranked as the most significant. These risks scored high in terms of likelihood, impact, and stakeholder concern, reflecting a broader unease with the pace and scope of AI integration without corresponding sustainability safeguards.

The interviews revealed important divergences between two primary stakeholder groups: Group 1, composed of industrial professionals in sustainability and innovation; and Group 2, comprising business representatives and technical experts from AI solution providers. Group 1 emphasized social and environmental risks more strongly, particularly workforce impacts and transparency issues. In contrast, Group 2 displayed confidence in the benefits of AI but acknowledged gaps in data availability, transparency, and regulatory clarity. What emerged from this divergence was a disconnection between sustainability ambition and digital innovation practice. Many firms lack robust frameworks to evaluate and govern the sustainability implications of AI integration. While digitalization and sustainability are both corporate priorities, they are frequently pursued in parallel rather than in alignment, creating missed opportunities and unmanaged risks.

Furthermore, the qualitative matrix helped illustrate that perceived risk severity is influenced not only by technical assessments but also by stakeholder values, roles, and proximity to implementation. This reinforces the importance of inclusive governance processes in risk management and calls into question the prevailing techno-solutionist narrative that AI inherently contributes to sustainable outcomes.

RQ2: How can industrial companies develop AI-enabled business models that align with sustainability principles?

Building on the risk assessment, the research introduced several novel applications of the SBM theory to industrial AI, offering five strategic pathways—Green AI and AIaaS, Inclusive AI Upskilling Platforms, Ethical AI Certifications and Privacy-First AI solutions—as potential levers for transforming risks into opportunities. These pathways extended the SBM literature by incorporating the unique characteristics of AI, such as data dependency, scalability, and algorithmic opacity, into sustainability-driven innovation.

Each strategy was aimed at addressing at least one of the key risks from the risk assessment. Green AI and AIaaS optimize model architectures for energy efficiency (model compression, energy-aware runtime parameters). They facilitate the partnership with carbon-neutral or green-certified data centers to reduce Scope 2 and 3 emissions. Circular AI Hardware Management establishes closed-loop take-back, refurbishment, and recycling programs for AI hardware assets. It incentivizes customers with loyalty schemes or service discounts for returning end-of-life equipment. Inclusive AI Upskilling Platforms foster the conduct of AI impact assessments to identify workforce displacement risks across demographics. It is aimed at co-creating reskilling curricula by partnering with community colleges and NGOs to build ‘AI-proof’ skills (e.g., system maintenance, data analysis, creative problem-solving). Ethical AI Certification Services & Privacy-First Solutions offer third-party audits against standards like IEEE 7000 and ISO/IEC 24028, awarding verifiable Ethical AI badges. They provide in-house toolkits for preliminary bias self-assessments, enabling modular entry points for projects of varying scale.

The stakeholders from both groups offered similar perspectives on the value pillars that should influence the integration of AI into business models. Thus, each proposed pathway leverages the four value pillars—transparency, stakeholder engagement, modularity, and partnerships—to transform identified risks into sources of competitive advantage. By embedding sustainability at the core of AI business models, industrial companies can shift from reactive compliance to proactive value creation.

6.2 Implications

This thesis contributes to the growing interdisciplinary discourse on responsible AI by centering sustainability within the risk assessment of industrial AI systems. While existing literature often addresses AI ethics or ESG impacts in silos, this study combines them into a unified risk framework that accounts for various sustainability dimensions. The stakeholder-informed matrix adds value by providing a structured yet flexible tool for qualitative risk prioritization. For industrial firms, the findings underscore the need to integrate sustainability assessments into AI development and deployment processes from the outset, not as an afterthought. The results suggest that companies must go beyond compliance and adopt proactive and systemic approaches to AI governance—ones that consider long-term sustainability impacts and stakeholder inclusion. Doing so can enhance resilience, reduce reputational risk, and unlock value from sustainable innovation. Moreover, for AI solution providers, the research highlights an emerging demand for ‘sustainability-ready’ products. As clients become more conscious of digital carbon footprints, suppliers will need to embed features such as energy-efficient model design, data privacy controls, and explainable AI tools into their offerings.

6.3 Recommendations

Based on the findings and stakeholder input, this thesis presents several actionable recommendations for companies, policymakers, and academic researchers.

For industrial companies and other sectors that are adopting AI, the sustainability risks posed by AI should be analyzed alongside other sustainability issues, not in a silo. This could include adding AI risk categories to materiality assessments, sustainability reporting, and auditing frameworks. It is crucial that cross-functional collaboration is fostered, especially since digital and sustainability teams often work in isolation. Firms should create cross-functional task forces or steering committees to jointly evaluate AI use cases, ensuring that sustainability is considered in procurement, development, and deployment stages. Few companies currently assess the full life cycle impacts of AI systems, from hardware manufacturing to data center energy use and software updates. Developing streamlined and scalable LCA methods for digital tools would allow firms to quantify environmental trade-offs more clearly. Additionally, transparency is foundational for accountability. Industrial firms should advocate for and invest in explainable AI techniques that provide clear rationales behind automated decisions, particularly in high-stakes applications like predictive maintenance or safety inspections. Procurement policies should include sustainability standards for AI providers, such as commitments to energy efficiency, bias mitigation, and data protection. These criteria can be built into supplier contracts and evaluated regularly.

For AI developers and AI technology providers, there is a need for a ground-up approach to sustainability. There is a need to integrate sustainability dimensions such as energy efficiency and carbon minimization into the software development lifecycle. Using model compression, federated learning, or edge computing strategies to reduce resource use where possible can make a vital difference. Providing B2B clients with dashboards or tools that track the environmental and social impacts of their AI systems can serve as a competitive differentiator. These metrics could include real-time energy use, carbon intensity, and data processing locations. Employees should participate in open-source sustainability standards and consortia. Collaborating with other players to develop pre-competitive frameworks for ethical AI could accelerate the adoption of best practices.

For policymakers and regulators, future AI legislation should incorporate sustainability considerations explicitly. This includes requiring environmental disclosures for high-risk systems and mandating social impact assessments in labor-intensive industries. Policymakers should support academic-industry research initiatives that explore AI's indirect effects on energy systems, labor markets, and environmental degradation. Public funding can help fill current data and methodology gaps. AI systems should have sustainability certifications that potentially evaluate emissions, human oversight, fairness, and data stewardship practices.

For researchers and academic institutions, there is great potential and use in developing courses that integrate sustainability, data ethics, and AI development. Future engineers and data scientists need to understand sustainability perspectives alongside technical skills. Moreover, there is a need for more empirical studies on how AI affects actual industrial processes, workers, and communities. Longitudinal research tracking sustainability outcomes over time would add rigor to the field. Creating and disseminating standardized tools for qualitative and quantitative sustainability risk assessments can empower smaller firms to evaluate AI risks more effectively without needing large in-house teams.

6.4 Future Research

While this study provides important insights, it considers a small sample size and focuses on the secondary industry under the broader umbrella of the industrial sector. Expanding the analysis to include perspectives from the extraction and commerce industries—where AI adoption dynamics and impacts may differ significantly, would offer a more holistic understanding on a sectoral level.

Further, the qualitative nature of the risk matrix limits its predictive power. Future studies could build quantitative models based on real-world AI deployment data to validate the perceived risks. There is also potential to integrate economic risk modeling with sustainability metrics to assess trade-offs more precisely.

Lastly, the dynamic nature of AI development means that risk categories and stakeholder priorities will evolve. Future research should treat risk assessment as a living process and explore how adaptive governance and continuous learning can be built into AI sustainability strategies.

6.5 Final Reflections

This thesis underscores that AI is neither inherently sustainable, nor unsustainable. Rather, it is shaped by the systems, incentives, and values embedded in its development and deployment. Rather than a purely technological or theoretical roadmap, the contribution lies in illustrating how sustainability risks and strategic transformation pressures shape organizational readiness, enabling more context-sensitive approaches to AI integration within the industrial sector.

As the industrial sector embarks on digital transformation journeys, the decisions made in the current landscape will reverberate across environmental systems, labor markets, and governance structures for decades to come. By surfacing the underexamined risks of industrial AI and proposing actionable SBM pathways, this research contributes to a more holistic understanding of how technology and sustainability can—and must—co-evolve. Building a just, green, and resilient digital future requires not only technical innovation, but also ethical imagination, stakeholder inclusion, and a willingness to challenge the status quo.

AI cannot be a diacatholican for global sustainability problems. As new technologies emerge, they offer great potential and promise in solving the world's most complex issues. However, as time passes, they often prove to be unsustainable. It is thus imperative that this innovation is carefully examined—for all its advantages and disadvantages—to establish a malleable path to harnessing its potential.

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Appendix

Appendix I. Interviewee Consent Form

Harnessing AI for Industrial Innovation: Sustainable Business Models and Risk Assessment

CONSENT FORM

This form is to ensure that you have been given information about *Harnessing AI for Industrial Innovation: Sustainable Business Models and Risk Assessment* and to give you an opportunity to confirm that you are willing to take part in this research. For all activities below, please indicate which applies to you (*checked box indicates consent*):

<input type="checkbox"/>	I have been familiarised with <i>Harnessing AI for Industrial Innovation: Sustainable Business Models and Risk Assessment</i> , I have had the possibility to ask questions and I have received satisfactory answers to my questions before being interviewed
<input type="checkbox"/>	As a research participant, I am aware of my right to withdraw participation at any time
<input type="checkbox"/>	I give my consent that the interview can be recorded in writing , translated and analysed
<input type="checkbox"/>	I give my consent that the interview can be audio- or video- recorded, transcribed using a third party speech-to-text transcription application, translated (if necessary) and analysed
<input type="checkbox"/>	I understand that the results of the research will be presented so that no information can be traced to me personally / I have been informed that pseudonymity of participants will be ensured
<input type="checkbox"/>	I give my consent that a record of my interview can be safely stored for future reference

Note: Your participation is voluntary. As an interviewee, you do not have to answer all the questions that are asked; you reserve the right to refuse or cease participation in the interview process without stating your reason and may request to keep certain materials confidential. In addition, you have the right to review any summary or synthesis of the interview at any time up until the data is actually published. There will be no monetary payment for participating in the research

Please, sign below to confirm your consent – digital signatures are possible:

	Participant(s)	Researcher(s)
Name(s) + ID		Ananya Ramaprasad ananya.nr25@gmail.com
Signature(s)		
Date(s)		

Appendix II. Interview Brief

Interview Brief

Ananya Ramaprasad

Harnessing AI for Industrial Innovation: Sustainable Business Models and Risk Assessment

About

Thank you for agreeing to participate in this interview. This document provides an overview of the research, the purpose of the interview, and what you can expect during our discussion.

I am conducting research for my thesis on integrating Artificial Intelligence (AI) into the industrial sector as a sustainability tool. Specifically, I am exploring

1. What considerations are important for decision making based on the same
2. Whether there is a comprehensive understanding of the implications of said decisions
3. The industrial climate within which AI is or is not being integrated
4. How the workforce perceives AI and what opportunities have been identified
5. Potential shifts in business models to integrate AI etc.

Your insights will help me understand the perceptions, challenges, and strategies that shape the adoption of AI in the industrial sustainability context. The research targets key stakeholders, including individuals and organizations within industrial companies who have integrated or have the potential to integrate AI in their business operations and product offerings for sustainability efforts. Please note that it is not required that you have experience handling AI in a professional capacity. One of the goals of the research is to understand workforce perceptions of AI. The insights from this interview will be coded/analysed and used for the thesis. The observations may also be included in the thesis but will remain anonymous.

Key Themes to be Discussed:

1. Perceptions of AI as a tool for sustainability
2. AI-integrated product offerings
3. AI in operations
4. Sustainability and ethical risks
5. Business Case for AI Integration

Interview Format & Logistics

- **Duration:** Approximately 30-45 minutes
- **Mode:** Video call/telephonic
- **Interviewer:** Ananya Ramaprasad
- **Confidentiality:** All responses will be kept confidential and used solely for research purposes unless otherwise agreed.
- **Recording & Notes:** The interview may be recorded for accuracy and transcription, with your consent.

Appendix III. Interview Question Guide (Group 1)

1. How does your company currently integrate AI into its circularity and sustainability initiatives?
2. In your opinion, what are the key drivers and barriers to AI adoption for sustainability in manufacturing?
3. Do you see AI as a tool for sustainability, optimization, or both? Why?
4. How is AI currently being used (or explored) in your company's product offerings? Do you actively promote the sale of these through the lens of using AI?
5. How is AI currently being used (or explored) in your company's circular economy strategies, such as waste reduction, resource efficiency, or material reuse?
6. Can you share any examples of AI-driven innovations in circularity within your company or industry?
7. What role do AI and digital technologies play in product lifecycle management and end-of-life strategies?
8. How does your company address any sustainability trade-offs of using AI?
9. What are the biggest risks associated with integrating AI into sustainable manufacturing?
10. How does your company assess the feasibility and constraints of AI-driven sustainability projects?
11. Do you believe there is sufficient knowledge and capacity within the manufacturing industry to leverage AI for circularity? Why or why not?
12. How does AI impact decision-making within your department? Are there any skills gaps preventing more effective AI adoption?
13. How do you ensure collaboration between sustainability teams and AI/technology teams to drive circularity?
14. How do you foresee AI transforming sustainable business models in the manufacturing sector over the next decade?
15. Are there any policy or regulatory changes that you believe could accelerate AI adoption for circularity?
16. If resources were not a constraint, how would you ideally integrate AI into your company's circular economy efforts?

Appendix IV. Interview Question Guide (Group 2)

1. Can you briefly describe your role and how you work at the intersection of AI and sustainability?
2. How would you define ‘sustainable AI’ in the context of industrial operations?
3. Which AI applications do you see gaining the most traction in industrial sustainability (such as predictive maintenance, energy optimization, emissions tracking)?
4. How mature are these AI solutions—are they still in pilot phases, or are they being widely deployed?
5. Can you share an example where AI meaningfully improved sustainability outcomes in an industrial setting?
6. What are the key environmental sustainability risks posed by AI in industry?
7. Are companies underestimating any social or governance risks—like bias in systems or lack of transparency?
8. What are the challenges industries face when trying to adopt AI sustainably?
9. How do you see AI contributing to or mitigating inequities in the industrial workforce?
10. What are the frameworks or business models you recommend for assessing AI’s impact on sustainability performance?