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Navigating the Trilemma of Sustainable Artificial Intelligence: Evidence from Germany

Master Thesis

Submitted by

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Abstract

The ongoing, pervasive ethical discourse surrounding the notion of "sustainable artificial intelligence (AI)" or *„nachhaltige KI"* in Germany underscores the necessity for AI systems and outcomes to be ecologically sustainable, socially accountable, and economically feasible. In theory, it would be arduous to optimise the three facets of sustainable development that include economic, social, and ecological sustainability, resulting in such a trilemma. This research uses Germany as an empirical case study for examining the current challenges related to sustainable AI efforts in Germany and how the country should navigate the trilemma of sustainable AI in the future. The study utilises a mixed-methods approach, incorporating qualitative and complementary quantitative data that is built on a conceptual framework drawn from three theoretical bases: (1) the three-pillar model of sustainability (Barbier, 1987); (2) 13 criteria for sustainable AI (Rohde et al., 2024); and (3) the contemporary theory of sustainable development (Lee & Park, 2021). The qualitative data were collected through semi-structured interviews and analysed using Atlas.ti, while the quantitative data were extracted from open-sourced datasets and visualised using Python and R. The results indicate that Germany is heavily prioritising ecological sustainability, moderately promoting social sustainability, and lagging behind in spurring economic sustainability in its overarching sustainable AI efforts. This justifies the conceptualised theoretical framework that signifies improbability to optimise the three sustainability facets, namely social, economic, and ecological sustainability, simultaneously and would solely be feasible to opt for two out of three. The way forward would be for Germany to develop and deploy its AI initiatives using its own approach, or what this study calls the "German way", with a huge emphasis on socio-ecological sustainability as the foundation that is amplified with equitable economic benefits for society.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

0.1 LIST OF ABBREVIATIONS

1. AI – Artificial Intelligence
2. DL – Deep learning
3. EnEfG – *Energieeffizienzgesetz*
4. EU – the European Union
5. ML – Machine learning
6. ROI – Return of Investment
7. VC – Venture Capital

1. INTRODUCTION

Discussions on sustainable artificial intelligence (AI), which in this context refers to the methodology of developing algorithms that exert machine learning (ML) and deep learning (DL) (Rane et al., 2024; Soori et al., 2023), frequently merely underscore the necessity for AI systems to be ecologically sustainable, socially accountable, and economically feasible. Achieving these three objectives simultaneously would be arduous and often spawn trade-offs and constitute a trilemma. This trilemma highlights a lingering challenge in AI development, where economic growth, social responsibility, and ecological ethics may be at odds. Although this challenge is theoretically acknowledged, empirical studies on how stakeholders navigate this trilemma in their efforts to devise and execute sustainable AI-related policies remain scarce.

Against this backdrop, the third wave of AI ethics debate is attempting to invoke the alignment of ecological awareness and environmental ethics in developing and deploying AI. The term "sustainable AI" was coined by AI ethicist Van Wynsberghe (2021), referring to 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. In other words, sustainable AI can be defined as AI systems designed and deployed to be environmentally sustainable, socially responsible, and economically viable (Schütze, 2024).

From an ethical AI perspective, sustainable AI encompasses two primary aspects, namely (1) the sustainability of AI and (2) the application of AI for sustainability. The former refers to designing AI systems using sustainable resources, while the latter emphasises leveraging AI as a tool to contribute to climate solutions. Nevertheless, addressing the obstacles linked to the sustainability of AI is a prerequisite before achieving AI for sustainability (Falk et al., 2024; Falk & van Wynsberghe, 2023), making the realisation of sustainable AI a significant challenge.

Aforementioned before, the notion of "sustainable AI" underscores the necessity for AI systems to be ecologically sustainable, socially accountable, and economically feasible. Nevertheless, achieving these three objectives simultaneously would be arduous and often spawn trade-offs and constitute a trilemma. This trilemma highlights a lingering quandary in Germany's AI development, where economic growth, social responsibility, and ecological ethics may be at odds. Although this challenge is theoretically acknowledged, empirical studies on how stakeholders navigate this trilemma in their efforts to devise and execute sustainable AI-related policies remain scarce.

In the context of Germany, there remains a notable challenge with balancing the scalability of economic, social, and environmental sustainability, potentially creating a "trilemma," despite Germany's superior performance on establishing a robust AI ecosystem compared to other EU member states. The latest report from the OECD decently portrayed the trilemma, underscoring such challenges as (1) insufficient measurement and mitigation of AI's environmental impacts; (2) the need to balance AI economic benefits with environmental protection; and (3) the growing energy consumption of data centres (OECD, 2024).

To this extent, the study aims to (1) identify challenges related to developing sustainable AI and (2) to identify the potential trilemma of fostering sustainable AI in Germany. In accordance with the research objectives, I have proposed two research questions. *First*, "*what challenges does Germany encounter in developing policies linked to sustainable AI?"* It is crucial to address this paramount but frequently overlooked question, particularly in light of the current issue of techno-social blindness among humans, which resulted in the inability to identify and confront the ethical implications of using emerging technologies such as AI (Vallor, 2022). Therefore, it is essential to identify the potential challenges Germany may face in advancing sustainable AI before formulating further strategies or policies to overcome any potential obstacles that could hinder the country's efforts to promote sustainable AI. In this context, the challenges refer to the operationalised concept of the Three-Pillar Model of Sustainability that is complemented by the 13 sustainability criteria of AI (Rohde et al., 2024) that will be further elaborated in the research design section.

Second, *"How can Germany navigate the trilemma of fostering sustainable AI?"* It is vital to raise this critical question, as Germany has to increase the scalability of AI-led innovations while simultaneously protecting the environment and promoting social equity. Nonetheless, theoretically, increasing the scalability of AI could potentially drive negative consequences on the environment and social equity. On the other hand, prioritising environmental protection and social fairness may potentially limit the vast economic advantages derived from harnessing AI. Given the existence of this trilemma, it becomes imperative to analyse approaches undertaken by relevant stakeholders in Germany to fostering sustainable AI that can balance economic, social, and environmental aspects.

To answer the questions, this study utilises a mixed-methods, incorporating qualitative and quantitative data with a case study approach built based on the traditional theoretical framework of Three-Pillar Model of Sustainability (Barbier, 1987) that outlines three primary facets of sustainable development, namely (1) economic sustainability; (2) ecological sustainability; and (3) social sustainability. This framework is supplemented by 13 criteria by Rohde et al (2024) contributing to each three pillars of sustainability in sustainable AI development. Data were collected primarily through a collection of interviews and primary academic sources.

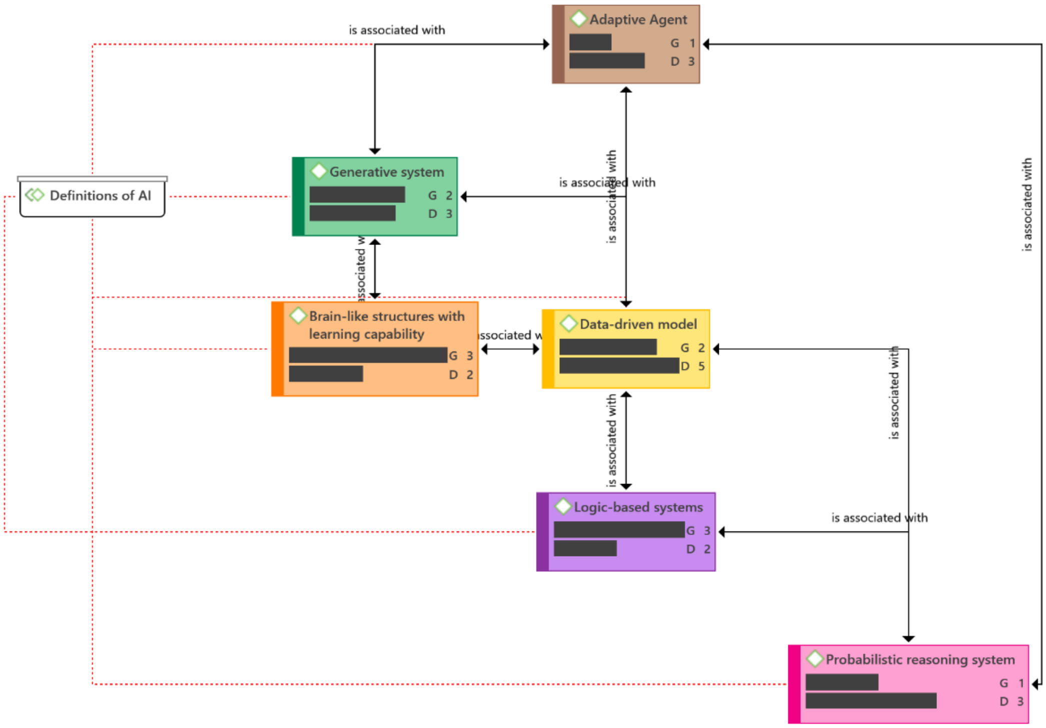
This research conducted semi-structured interviews with relevant stakeholders. Subsequently this study used Atlas.ti to systematically code and interpret the interview transcripts accordingly to identify particular themes and patterns from the interview results. On top of that, it exerted relevant open-source datasets linked to (1) the use of AI in the public and private sector and (2) AI compute and climate change in Germany, sourced from Eurostat, OECD AI Policy Observatory (OECD.AI), Statista, and the German Environment Agency (UBA). Afterwards, this research yielded explainable charts to illustrate the quantitative phenomena using python and R, thus supplementing the qualitative data and arguments.

The thesis contains sections as follows. *First*, the section on systematic literature review (SLR) extrapolates relevant academic articles published within the timeframe of 2021 until 2025 to yield foundational definitions and fundamental concepts embodied in the terminology of sustainable AI. *Second*, details on methodology and research design used in the study, along with limitations of the research. *Third*, a presentation on qualitative and complementary quantitative data in addressing the research questions. *Fourth*, in-depth and critical discussion pertinent to the presented results in the previous section. *Sixth*, a conclusion and recommendations for future research linked to the study.

2. LITERATURE REVIEW

2.1 Defining Artificial Intelligence (AI)

Figure 2.1. Definitions of Artificial Intelligence (AI)



Source: Author’s formulation (2025)

Since the first public introduction of the term “artificial intelligence” or in short “AI” in 1950 delineated by Alan Turing in his renowned paper “Computing Machinery and Intelligence” (Turing, 1950), there have evolved a plethora of definitions and terminologies classified this very emerging technology. To encapsulate, the terminology of AI can be grouped into six fundamental categories (Table 2.1), namely (1) a logic-based systems or renowned as “Symbolic AI” (Cram & Newell, 2016; Turing, 1950); (2) a brain-like structures with learning capability (Frank Rosenblatt, 1958; Geoffrey Hinton et al., 1986; Yann LeCun et al., 1989); (3) a probabilistic reasoning system (Judea Pearl, 1988); (4) a data-driven model (Vladimir Vapnik and Alexey Chervonenkis, 1971; Ian Goodfellow et al., 2014); (5) an adaptive agent (Richard Sutton & Andrew Barto, 1998); and (6) a generative system (Ashish Vaswani et al., 2017; Ian Goodfellow et al., 2014).

Alan Turing's pivotal research paper, *Computing Machinery and Intelligence* (1950), introduced the Turing Test as a criterion for assessing machine intelligence, building a groundbreaking foundation for the evaluating the performance of AI capabilities. The term “Artificial Intelligence” subsequently publicly used by a group of researchers in *A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence* (McCarthy et al., 1955) for advancing research on logic-based AI systems. In particular, this research focuses on the term AI as the methodology of developing algorithms that exert machine learning (ML) and deep learning (DL) (Rane et al., 2024; Soori et al., 2023).

Table 2.1. Six Primary Definitions of Artificial Intelligence

No.	Definition of AI	Key Scientific Paper	Fundamental Development
1.	AI as logic-based systems or renowned as "Symbolic AI"	Computing Machinery and Intelligence (Alan Turing, 1950)	Introduced the method of the "Turing Test" as a criterion for machine intelligence
		A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence (John McCarthy et al., 1955)	The first scientific article that coined the term "Artificial Intelligence" and proposed logic-based AI research
		The Logic Theory Machine: A Complex Information Processing System (Allen Newell and Herbert Simon, 1956)	Spearheaded one of the initial AI-driven programs that could analyse mathematical theorems
2.	Probabilistic reasoning system	The Perceptron: A Probabilistic Model for Information Storage and Organisation in the Brain (Frank Rosenblatt, 1958)	Introduced the "Perceptron" as the first model for developing artificial neural networks
		Learing Representations by Back-Propagation Errors (Geoffrey Hinton, David Rumelhart, and Ronald Williams, 1986)	Introduced the training of multi-layer neural networks through "backpropagation."
		Backpropagation Applied to Handwritten Zip Code Recognition (Yann LeCun et al., 1989)	Demonstrated the application of Convolutional Neural Networks (CNNs)
3.	AI as a multifaceted system with ability to reason under uncertainty	Probabilistic Reasoning in Intelligent Systems: networks of Plausible Inference (Judea Pearl, 1988)	Introduced the Bayesian networks for reasoning under uncertainty
4.	AI as a data-driven model	On the Uniform Convergence of Relative Frequencies of Events to Their Probabilities (Vladimir Vapnik and Alexey Chervonenkis, 1971)	Developed the fundamental theoretical foundation for support vector machines (SVMs)

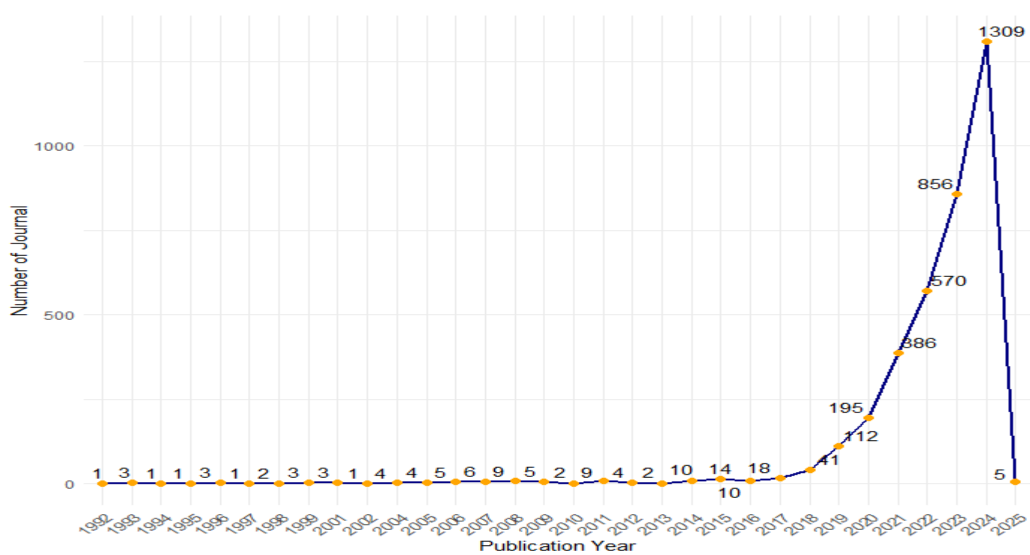
No.	Definition of AI	Key Scientific Paper	Fundamental Development
		Generative Adversarial Nets (Ian Goodfellow et al., 2014)	Coined the term and concept of "Generative Adversarial Networks (GANs)" as a cornerstone of the recent generative model.
5.	AI as an adaptive agent	Reinforcement Learning: An Introduction (Richard Sutton & Andrew Barto, 1998)	Coined the term "Reinforcement Learning" as a fundamental AI concept for agent-based learning mechanism.
6.	AI as generative system	Attention Is All You Need (Ashish Vaswani et al., 2017)	Introduced the Transformer architecture, contributing to the revolusionisation of NLP models, including GPT
		Generative Adversarial Nets (Ian Goodfellow et al., 2014	Proposed the concept of GANs as foundational AI-generated content

Source: Author's formulation (2025)

2.2 Grasping the notion of Sustainable AI

The term "sustainable AI" was coined by AI ethicist Van Wynsberghe (2021), referring to a movement to foster change in the entire lifecycle of AI products (e.g., idea generation, training, re-tuning, implementation, governance) towards greater ecological integrity and social justice. In other words, sustainable AI can be defined as AI systems designed and deployed to be environmentally sustainable, socially responsible, and economically viable (Schütze, 2024).

Figure 2.2. Number of Published Journals on Sustainable AI (1992 – Present)



Source: Author's formulation (2024)

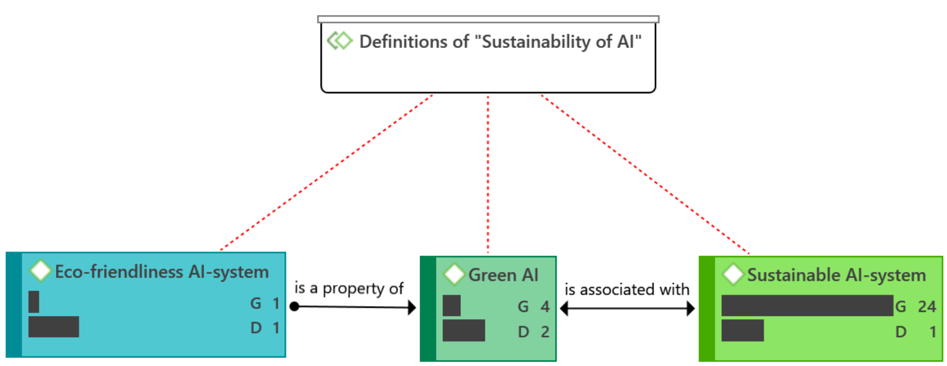
From an ethical AI perspective, sustainable AI encompasses two primary aspects, namely (1) the sustainability of AI and (2) the application of AI for sustainability (Figure 1). The former refers to designing AI systems using sustainable resources, while the latter emphasises leveraging AI as a tool to contribute to climate solutions. Nevertheless, addressing the obstacles linked to the sustainability of AI is a prerequisite before achieving AI for sustainability (Falk et al., 2024; Falk & van Wynsberghe, 2023a), making the realisation of sustainable AI a significant challenge.

Based on search on Web of Science, a total of 1,309 academic articles on Sustainable AI has been published between 1992 – 2024, with the year of 2024 becomes the culminate period of the trend (Figure 2.2). The current state of literature on sustainable AI primarily discusses over AI ethics linked to environmental impacts, focusing on two major themes: (1) "AI for sustainability" (Falk & van Wynsberghe, 2023a, 2023b; van Wynsberghe, 2021) and (2) "Sustainability of AI" (Coeckelbergh, 2020, 2022; Schütze, 2024.). To comprehensively comprehend the term "Sustainable AI," it is imperative delve into these two fundamental edifices of the term.

2.2.1 Sustainability of AI

Literatures vary in converging the core definition on the term "Sustainability of AI," with three most common used terminologies comprise (1) sustainable AI-system (Almeida et al., 2024; Alzoubi & Mishra, 2024; Balan, 2024; Barbierato & Gatti, 2024; Biggi et al., 2025; Dash, 2025; Eilam et al., 2023; Genovesi & Mönig, 2022; Jay et al., 2024; Kumar et al., 2024; Leuthe et al., 2024; Perucica & Andjelkovic, 2022; Rohde et al., 2024; Sikand et al., 2023; Trinh et al., 2024; van Wynsberghe et al., 2022; Wang et al., 2024); (2) green AI (Bolón-Canedo et al., 2024; Tabbakh et al., 2024; Verdecchia et al., 2023); and (3) eco-friendliness AI-system (Vartziotis et al., 2024).

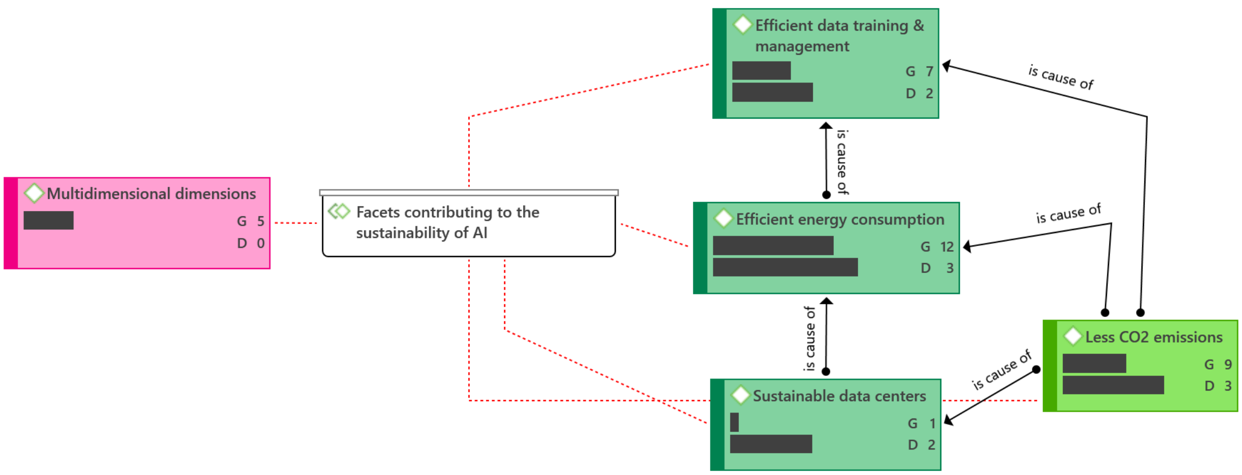
Figure 2.3. Definitions of Sustainability of AI



Source: Author's formulation (2025)

Out of 31 articles, the term “Sustainable AI-system” stands out as the most popular utilised by authors (24 codes), followed by “Green AI” (4 codes), and “Eco-friendliness AI-system” (1 code). Articles that applied the term “Eco-friendliness AI-system” represents an attribute of “Green AI,” while the notion of “Green AI” is significantly correlated with “Sustainable AI-system” (Figure 2.3). This underscores the divergence in defining the term “Sustainability of AI” across researchers worldwide, yet highlights the commonalities in comprehending the term as an AI-system with a compatible sustainable resource embodied throughout its lifecycle (Balan, 2024; Leuthe et al., 2024; Rohde et al., 2024; Sikand et al., 2023).

Figure 2.4. Facets contributing to the Sustainability of AI



Source: Author’s formulation (2025)

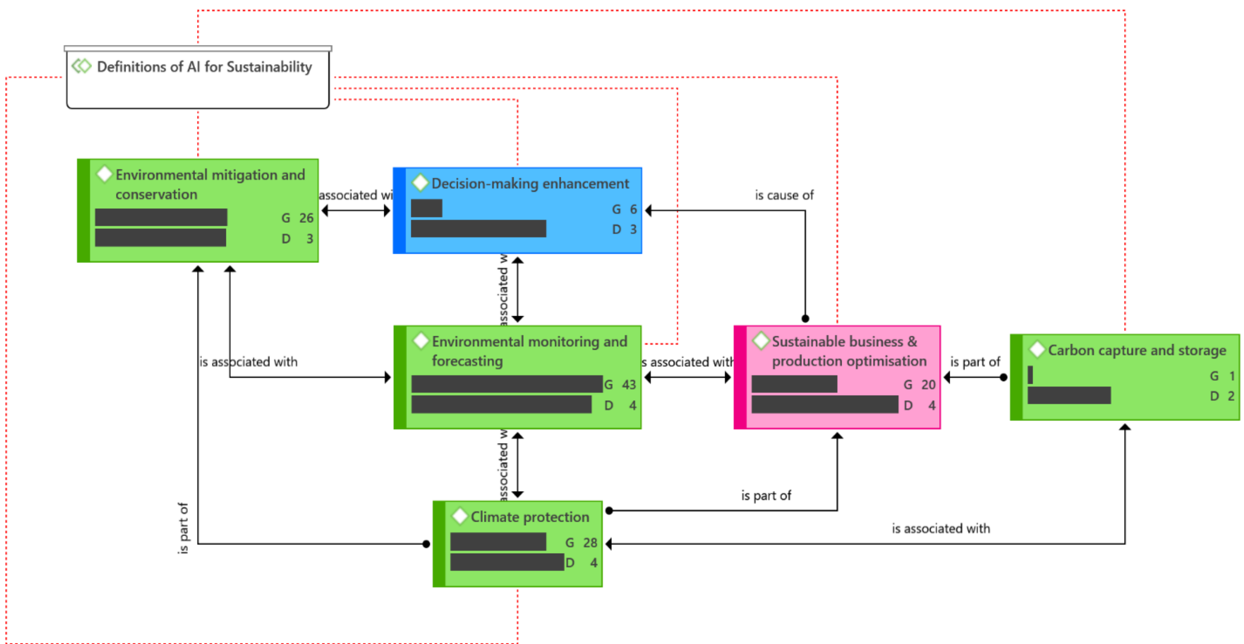
Furthermore, among several facets contributing to the sustainability of AI, there is a stark divide between those who are categorised under the umbrella of (1) environmental-related factors (coloured green) and (2) multidimensional dimensions (coloured pink) as portrayed in Figure 2.4. The former’s emphasis lies in the considerable consequences of efficient data training and management (Almeida et al., 2024; Bolón-Canedo et al., 2024; Jay et al., 2024), efficient energy consumption (Biggi et al., 2025; Bolón-Canedo et al., 2024; Castellanos-Nieves & García-Forte, 2023a; Ofek & Maimon, 2023; Tabbakh et al., 2024; Vartziotis et al., 2024), and sustainable data centres to abate CO2 emissions that can exacerbate the climate change. While the later comprises multi-factors that also may significantly contribute to the realisation of sustainability of AI, including socio-economic and ethical resource management (Balan, 2024; Dias & Lunga, 2022).

2.2.2 AI for Sustainability

Leveraging AI for sustainability weights more on the utilisation of AI-led systems to foster sustainable efforts in the context of economy, social, and environment as depicted in Figure 2.5 with colours of pink, blue, and green, respectively. In practice, this phenomenon is considerably linked to tackling environmental-related challenges, encompassing (1) environmental monitoring and forecasting (Abba et al., 2023a; Ahmed et al., 2024; Alam et al., 2025; Amjad et al., 2023; Aryal, 2022; Bibri et al., 2022; Choubey et al., 2024; Davalagi et al., 2022; Dostatni et al., 2023; Falk & van Wynsberghe, 2023a; Hussein et al., 2025; Khanmohammadi et al., 2023; Low et al., 2022; Nakhaei et al., 2023; Nassef, 2023; Neethirajan, 2023; Pastor-Escuredo et al., 2022; Renganayagalu et al., 2024; Salla et al., 2025; Senthil Pandi et al., 2025; Sheng et al., 2025; Shukla et al., 2024; Subbiah et al., 2024; Tedeschi, 2022; Tiyasha et al., 2021; Udoh et al., 2024; Valencia Diaz et al., 2022a; wang et al., 2024; S. Wang et al., 2023; Xu & Ge, 2024; Yavari et al., 2023; Zandifaez et al., 2023), (2) climate protection (Ahmed et al., 2024; Alam et al., 2025; Aryal, 2022; Castellanos-Nieves & García-Forte, 2023a; Cicceri et al., 2023; Dimitrijević, 2023; Garlik, 2022; Gheysari et al., 2021; Jurj et al., 2023; Li et al., 2024; Mahmood et al., 2024; Nassef, 2023; Qing et al., 2024; Rodríguez-Gracia et al., 2023; Shrestha et al., 2023; Shukla et al., 2024; Uriarte-Gallastegi et al., 2024; wang et al., 2024; Yavari et al., 2023), (3) environmental mitigation and conservation (Dimitrijević, 2023; Garlik, 2022; Gheysari et al., 2021; Gülmez, 2024; Khanmohammadi et al., 2023; Neo et al., 2022; Neri et al., 2024; Pastor-Escuredo et al., 2022; Qing et al., 2024; Salla et al., 2025; Savazzi et al., 2021; Senni et al., 2025; Sheng et al., 2025; Subbiah et al., 2024; Tsai & Yuan, 2025; Udoh et al., 2024; Valencia Diaz et al., 2022b; P. Wang et al., 2023; Zafar et al., 2023), and (4) carbon capture and storage (Li et al., 2024; Rycroft et al., 2023). In sum, these endeavours are ultimately intended to bolster climate protection and diminish the disastrous impacts that may be yielded by climate change, with an onus lies in the decision maker to produce pro-sustainability policies.

Moreover, AI is utilised to promote sustainable business production and optimisation (Castellanos-Nieves & García-Forte, 2023b; Codeluppi et al., 2021; Dostatni et al., 2023; Hussain et al., 2024; Mahmood et al., 2024; Onu et al., 2023; Senthil Pandi et al., 2025; Solomon & Crawford, 2021; Tedeschi, 2022; Tsai & Yuan, 2025; Uriarte-Gallastegi et al., 2024; wang et al., 2024; S. Wang et al., 2023; Xue & Lai, 2024; Zandifaez et al., 2023) in the realms of inducing economic sustainability, whereas the system drives decision-making enhancement (Abba et al., 2023a; Bibri et al., 2022; Chakraborty et al., 2021; Piras et al., 2024; Shrestha et al., 2023) simultaneously to inflict betterment in policy and decision outcomes. The former is critically linked to corroborate environmental mitigation and conservation and is pivotal to optimise sustainability practices in business and production processes. While the latter is practically implementing carbon capture and storage as part of the strategy to boost sustainable business and manufacturing.

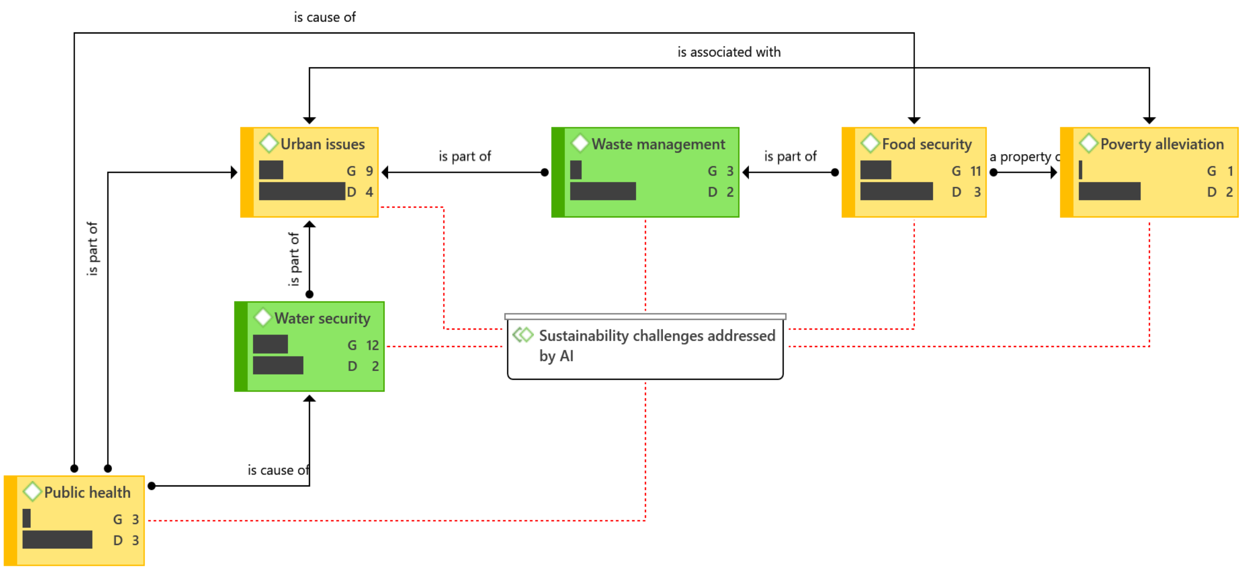
Figure 2.5. Definitions of AI for Sustainability



Source: Author’s formulation (2025)

Harnessing AI for sustainability is tremendously induced by the critical necessity to tackle numerous persisting sustainability challenges in society, including (1) environmental-related issues like waste management (Choubey et al., 2024; Funchal et al., 2022; Valencia Diaz et al., 2022b) and water security (Abba et al., 2023b; Chakraborty et al., 2021; Hussein et al., 2025; Lu et al., 2023; Nakhaei et al., 2023; Tiyasha et al., 2021; wang et al., 2024) and (2) social challenges such as urban issues (Abba et al., 2023b; Al-Masri & Curran, 2017; Arsiwala et al., 2023; Bibri et al., 2024; Davalagi et al., 2022; Garlik, 2022; Gupta & Tandon, 2023; Low et al., 2022; Pastor-Escuredo et al., 2022), food security (Ardèvol-Abreu et al., 2020; Castellanos-Nieves & García-Forte, 2023a; Funchal et al., 2022; Gülmez, 2024), poverty alleviation (Codeluppi et al., 2021; Dimitrijević, 2023; Neethirajan, 2023; Ouafiq et al., 2022; Verma, 2024), and public health (Davalagi et al., 2022; Neo et al., 2022; Verma, 2024). Environmental-related issues, which are coloured with green, are primarily part of urban issues. While social challenges (yellow coloured) are evidently interlinked and may be part of and caused by environmental-related menaces (Figure 2.6).

Figure 2.6. Sustainability challenges addressed by AI

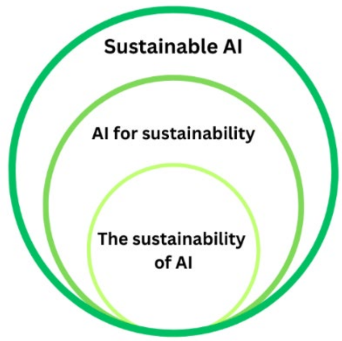


Source: Author's formulation (2025)

2.2.3 Sustainable AI

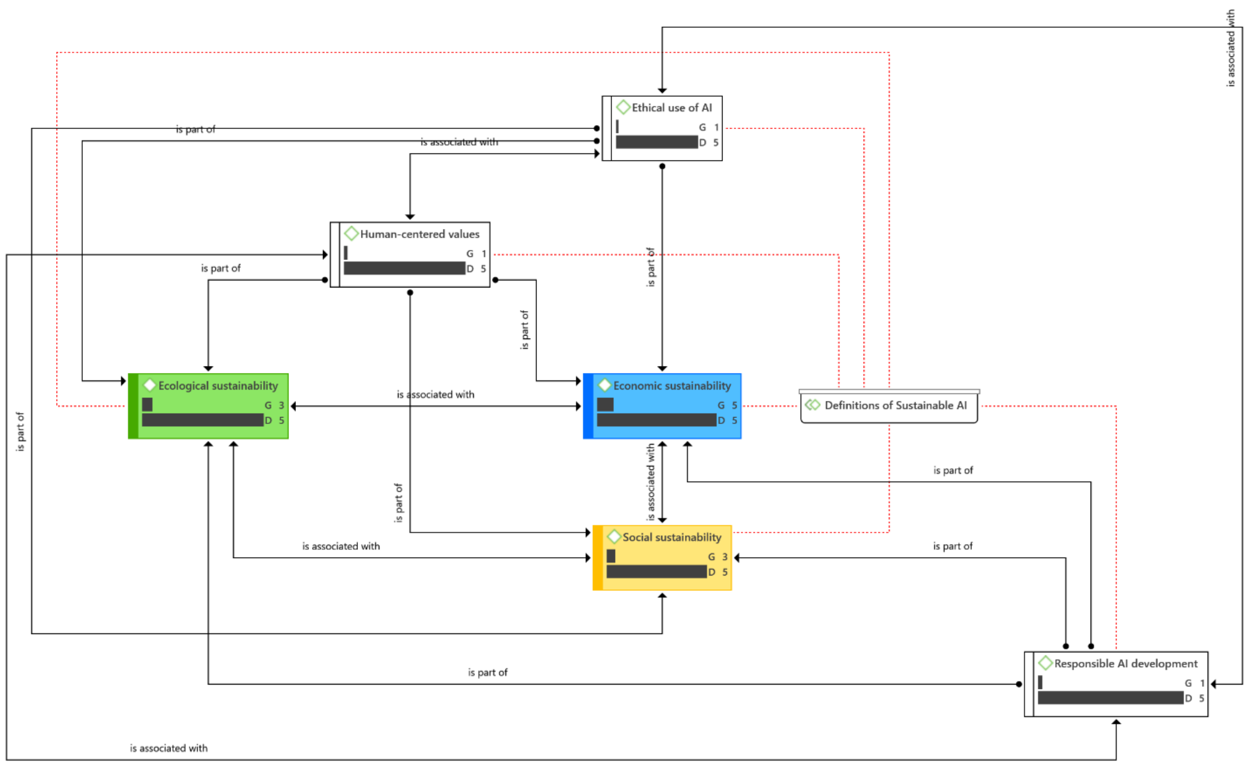
Against this backdrop, the third wave of AI ethics debate is attempting to invoke the alignment of ecological awareness and environmental ethics in developing and deploying AI. The term "sustainable AI" was coined by AI ethicist Van Wynsberghe (2021), referring to a movement to foster change in the entire lifecycle of AI products (e.g., idea generation, training, re-tuning, implementation, governance) towards greater ecological integrity and social justice. Nevertheless, addressing the obstacles linked to the sustainability of AI is a prerequisite before achieving AI for sustainability (Falk et al., 2024; Falk & van Wynsberghe, 2023a), making the realisation of sustainable AI a significant challenge.

Fig 2.7. The Concept of Sustainable AI



Source: Author's formulation, 2024

Figure 2.8. Definitions of Sustainable AI



Source: Author's formulation (2025)

Aforementioned before, the current literature remains scarce outlining the notion of "Sustainable AI" as the outcome of the fusion of two fundamental facets of its embodiment: (1) sustainability of AI and (2) AI for sustainability. Drawing from relevant articles, research on this notable area shed light on three primary edifices of sustainable AI, namely (1) ecological sustainability (Bolte, 2023; VanWynsberghe, 2021); (2) economic sustainability (Bolte, 2023; VanWynsberghe, 2021; Chover, 2023; Wehlmann, 2022); and (3) social sustainability (Bolte, 2023). In other words, sustainable AI can be defined as AI systems designed and deployed to be environmentally sustainable, socially responsible, and economically viable (Schütze, 2024). (Figure 2.8).

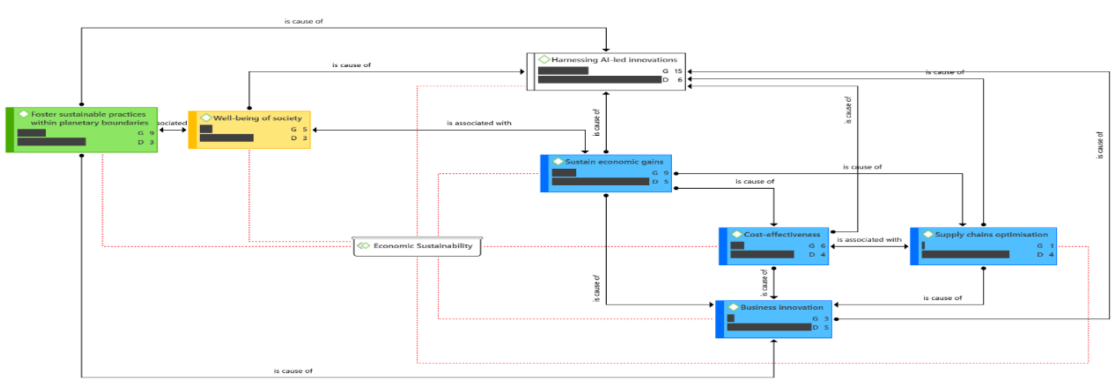
Theoretically, the three pillars of sustainable AI considerably intersected with none of the elements have less contribution compared to others in underpinning sustainable AI. In practice, another three pivotal external factors parallelly supplement the embodiment of sustainable AI, encompassing (1) human-centered values (Schutze, 2024); ethical use of AI (Schutze, 2024); and (3) responsible AI development (Schutze, 2024). However, the reality frequently reflects that optimising these three elements simultaneously is improbable, resulting in a trilemma.

2.3 Unravelling Facets of Sustainable AI

2.3.1 Economic sustainability

The first quandary of the trilemma is economic sustainability, which is perceived as part of multidimensional notions to impel economic growth (Alsabt et al., 2024; Arundel et al., 2019; Dimitrijević, 2023; Siddik et al., 2025; Silva & Rosamilha, 2024; Sjödin et al., 2023) while safeguarding planetary boundaries simultaneously (Balcıoğlu et al., 2024; Roberts et al., 2024; Rohde, Wagner, Meyer, et al., 2023; Soo et al., 2024). AI functions as a mainstay in yielding positive outputs and outcomes through innovations to spur economic productivity and gains, as well as to bolster sustainable practices (Alturif et al., 2024; Arun et al., 2025; Balcıoğlu et al., 2024; Dadebo et al., 2023; Gündüzyeli, 2024; Hong & Xiao, 2024; Rohde, Wagner, Reinhard, et al., 2023; Siddik et al., 2025; Verdecchia et al., 2023; Wei & Cheng, 2022). As a result, the expected ultimate objective of uplifting the well-being of society can be obtained (Dimitrijević, 2023).

Figure 2.9. Grasping economic sustainability with keyword search of Economic Sustainability AND Sustainable AI



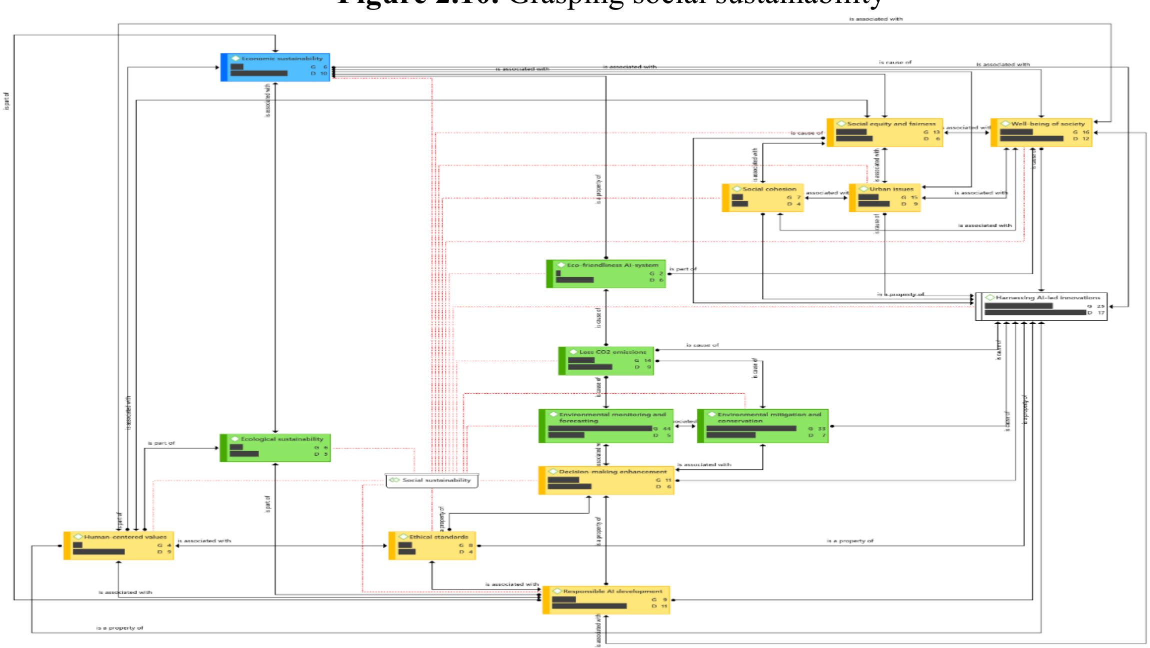
Source: Author’s formulation (2025)

In practice, research showcase that promoting economic sustainability dovetails to economic-related attributions, encompassing (1) sustain economic gains (Alsabt et al., 2024; Arun et al., 2025; Balcıoğlu et al., 2024; Dimitrijević, 2023; Siddik et al., 2025; Sjödin et al., 2023); (2) cost-effectiveness (Balcıoğlu et al., 2024); (3) supply chain optimisation (Soo et al., 2024) ; and (4) business innovation (Dimitrijević, 2023; Sjödin et al., 2023). These four economic advantages are often linked each other and primarily driven by the utilisation of AI-led innovation in the business or production lifecycle. Apart from their profitable impact on businesses, it shows correlation in inflicting social and environmental benefits simultaneously (Figure 2.9).

2.3.2 Social sustainability

As a part of multidimensional concept, social sustainability in the scope of AI development and deployment implies attempts on improving societal (Arpaci, 2024; Forsten-Astikainen et al., 2017; Habibipour, 2024; Khosravy et al., 2024; Meņšikovs et al., 2024; Samuel et al., n.d.; Saxena et al., 2023; Suo et al., 2024), economic (Alahmari et al., 2022; Dadebo et al., 2023; Meņšikovs et al., 2024; Rohde, Wagner, Reinhard, et al., 2024; Zhang & Guo, 2023), and environmental (Alahmari et al., 2022; Hao & Demir, 2024; Hermann et al., 2021; Meņšikovs et al., 2024; Oyadeyi & Oyadeyi, 2025; Rehman & Umar, 2024; Zhang & Guo, 2023) positive impacts to the society, with a greater weight on social values (Khosravy et al., 2024).

Figure 2.10. Grasping social sustainability



Source: Author’s formulation (2025)

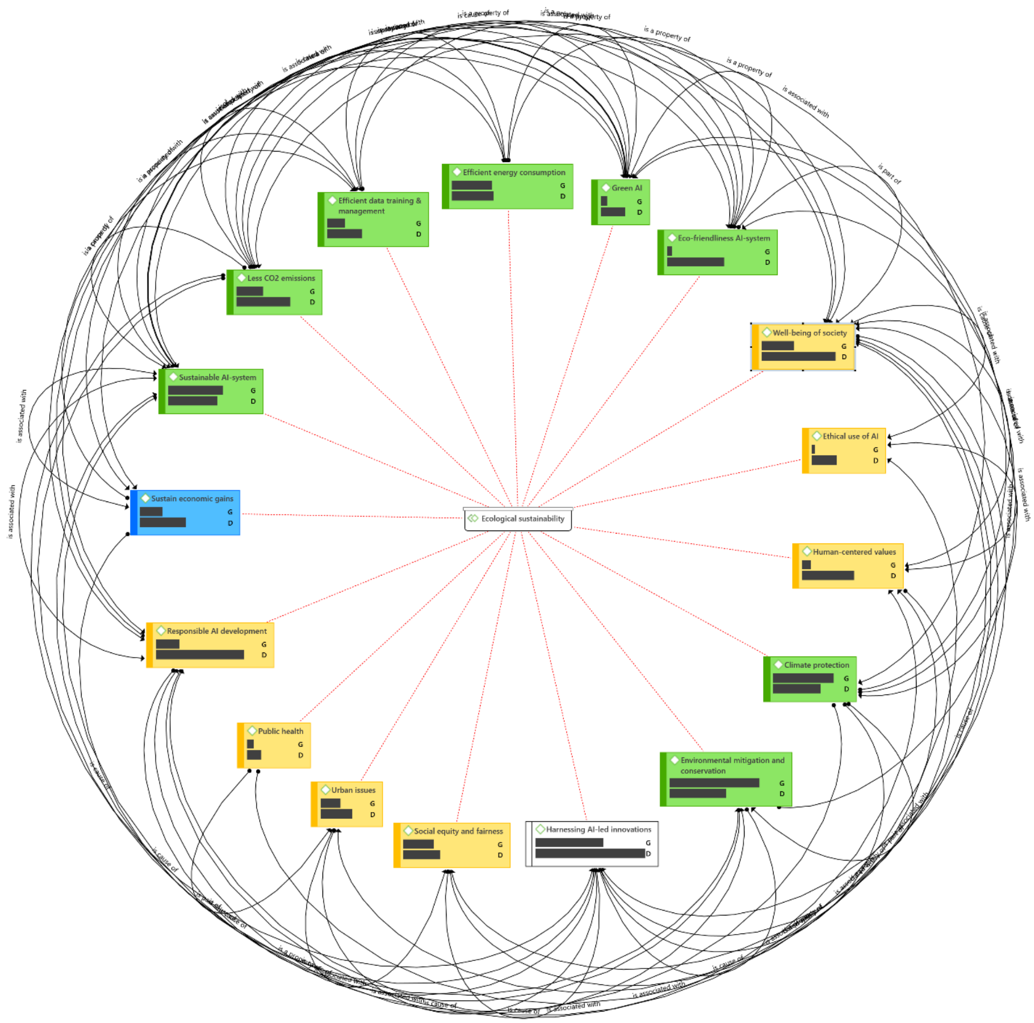
Fostering social sustainability is substantially intertwined with ecological sustainability principles (Khosravy et al., 2024; Rehman & Umar, 2024), which fundamentally entrenched in the simultaneous use of eco-friendliness AI-system. As a result, spurring social sustainability yield ecological benefits (Rehman & Umar, 2024) to the society that may include environmental monitoring and forecasting and environmental mitigation and conservation, with an utmost goal to abate the emission (Oyadeyi & Oyadeyi, 2025). Moreover, social sustainability approach has a correlation with promoting economic sustainability, yet with a less significant interlinks, epitomised in Figure 2.10.

The utilisation of AI-led innovations, which cornered in (1) human-centred values (Khosravy et al., 2024); (2) ethical standards (Arpaci, 2024; Habibipour, 2024; Hao & Demir, 2024; Khosravy et al., 2024; Rohde, Wagner, Reinhard, et al., 2023; Suo et al., 2024); (3) responsible development (Al-Emran et al., 2025; Arpaci, 2024; Habibipour, 2024; Meņšikovs et al., 2024) and (4) decision-making enhancement by policymakers (Khosravy et al., 2024; Wilson & van der Velden, 2022), becomes a mainstay in driving societal impacts as depicted in Figure 2.10. Benefits aimed to the society encompass social equity and fairness (Al-Emran et al., 2025; Arpaci, 2024; Habibipour, 2024; Hao & Demir, 2024; Oyadeyi & Oyadeyi, 2025; Pansoni et al., 2023) and social cohesion (Alahmari et al., 2022; Khosravy et al., 2024; Rohde, Wagner, Reinhard, et al., 2023; Saxena et al., 2023; Wilson & van der Velden, 2022) with ultimate objectives to surmount urban issues (Arpaci, 2024; Dadebo et al., 2023; Hao & Demir, 2024; Khosravy et al., 2024; Oyadeyi & Oyadeyi, 2025) and uplift the well-being of society (Almeida et al., 2024; Dadebo et al., 2023; Habibipour, 2024; Saxena et al., 2023; Suo et al., 2024) as a whole.

2.3.3 Ecological sustainability

Applying ecological sustainability implies a vast emphasis on corroborating responsible human-ecology relationship (Bolte et al., 2022; Francisco, 2023; wang et al., 2024; Xu & Ge, 2024) through ubiquitous exert of technologies (Nicodeme, 2021; Tiutiulnikov et al., 2023). In other words, this facet of sustainability in the realm of AI advancement and deployment is tightly entwined with the aforementioned social sustainability, which sheds less light on boosting economic gains (Ficko et al., 2025). Figure 2.11 implies the relationships where the attributions on ecological (coloured green) and social (coloured yellow) factors have a roughly equal links compared to economic-linked category (coloured blue) that only appear once.

Figure 2.11. Grasping social sustainability with keyword search of Economic Sustainability AND Sustainable AI



Source: Author's formulation (2025)

In practice, AI-led innovations commonly embedded in a diverse technological artifact with identical functions, comprising (1) sustainable AI-system (Raman et al., 2024); (2) green AI (Raman et al., 2024); and (3) eco-friendliness AI system (Tiutiulnikov, 2023). Each of these types contribute to preserve the environment through environmental mitigation and conservation (Wang, 2023; Xu, 2024; Schmitt, 2024; Castelanos, 2023; Alsamhi, 2024), efficient data training and management (Tiutliulnikov, 2023), and efficient energy consumption (Tiutliulnikov, 2023; Schmitt, 2024; Castelanos, 2023). As a result, harnessing AI-based technologies in the context of ecological sustainability will ultimately curtail CO2 emission (Castelanos, 2023; Schmitt, 2024; Wang, 2023; Tiutulnikov, 2023) and promote more climate protection (Alsamhi, 2024; Xu, 2024; Nicodeme, 2021; Tiutliunikov, 2023).

Furthermore, ecological sustainability is perceived as a paramount element buoyed by responsible AI development practices that are linked to social sustainability values (Bolte, 2023; Xu, 2024; Tiutulnikov, 2023). This relationship is associated with human-centred values (Xu, 2024) and ethical use of AI (Bolte, 2023), and realising social equity and fairness (Bolte, 2023), which practically aid to address urban (Tiutliunikov, 2023) and public health (Alsamhi, 2024) issues. Not to mention, the culmination of enhancing social sustainability, to uplift well-being of society, is also considered as the outcome of the exert of eco-friendliness AI system, marking it inseparable for ecological and social sustainability to be practiced simultaneously.

2.4 Navigating the Trilemma of Sustainable AI

Academic articles remain measly in discussing the trilemma of sustainable AI, which in general may refer to the trade-offs between three primary aspects of AI systems, namely (1) social; (2) economic; and (3) environmental facets. In the contemporary theory of sustainable development, optimising the three objectives will be at odds each other, making it solely feasible to opt two out of three facets at the same time. For instance, spurring economic growth frequently yield harmful consequences for social equity and environmental preservation. Conversely, prioritising social equity, including social fairness and justice, and environmental protection may impede economic growth (Lee & Park, 2021).

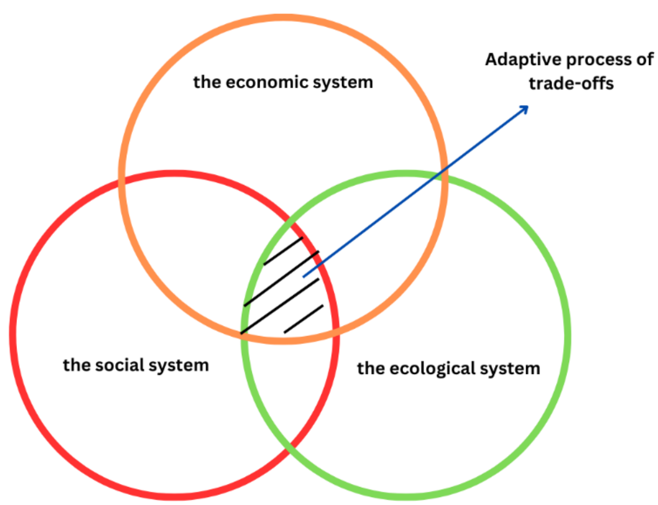
When it comes to searching for keywords "The Trilemma of Sustainable AI *AND* Sustainability of AI *AND* AI for Sustainability *AND* Germany", none of academic paper ever published until 2025. Mirroring from the state of art, there is a loophole in research on empirical evidence, particularly in discussing a case study approach to analyse how countries, such as Germany, navigate the trilemma of sustainable AI amidst its current rapid AI advancement and deployment. This study would yield a significant impact since there are still lingering problems with balancing the scalability of economic, social, and environmental sustainability, potentially creating a "trilemma," despite Germany's superior performance on establishing a robust AI ecosystem compared to other EU member states.

3. METHODOLOGY

3.1 Research Design

This study utilised a mixed-methods approach, incorporating qualitative and quantitative data collection and analysis (Creswell, 1999) and is built by combining three primary relevant frameworks. *First*, the traditional theoretical framework of Three-Pillar Model of Sustainability Barbier (1987) outlines three primary facets of sustainable development, namely (1) economic sustainability; (2) ecological sustainability; and (3) social sustainability. (Figure 3.1).

Figure 3.1. Three-Pillar Model of Sustainable Development



Source: Author's formulation based on Barbier (1987), 2024

The initial objective of this particular theory was to serve as a critical reflection on the promotion of meaningful growth in society, by establishing a robust commitment to preserve the environment and promote the rational use of resources simultaneously (Barbier, 1987). Moreover, Barbier also criticised previous economic development for its exclusive focus on maximising economic gains, neglecting the significance of cultivating adaptive trade-off processes, and resulting in a trilemma, given the high likelihood of simultaneously optimising all three variables.

Table 3.1. Sustainability Criteria for AI by Rohde et al., 2024

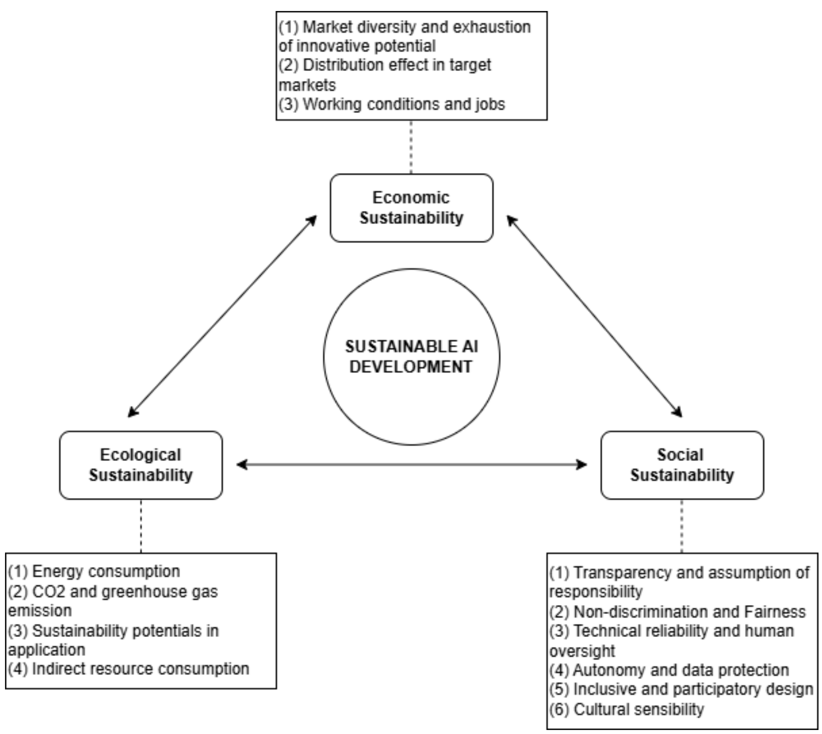
Grouping	Criteria
Social sustainability	• Transparency and assumption of responsibility • Non-discrimination and fairness

Grouping	Criteria
	• Technical reliability and human oversight • Autonomy and data protection • Inclusive and participatory design • Cultural sensibility
Economic sustainability	• Market diversity and exhaustion of innovative potential • Distribution effect in target markets • Working conditions and jobs
Ecological sustainability	• Energy consumption • CO2 and greenhouse gas emission • Sustainability potentials in application • Indirect resource consumption

Source: Rohde et al (2024)

Second, to complement the traditional framework, this study adopted the 13 criteria contributing to each three pillars analysed by Rohde et al (2024), giving clarity to what factors should be considered when analysing three pillars of sustainability in sustainable AI development (Figure 3.2).

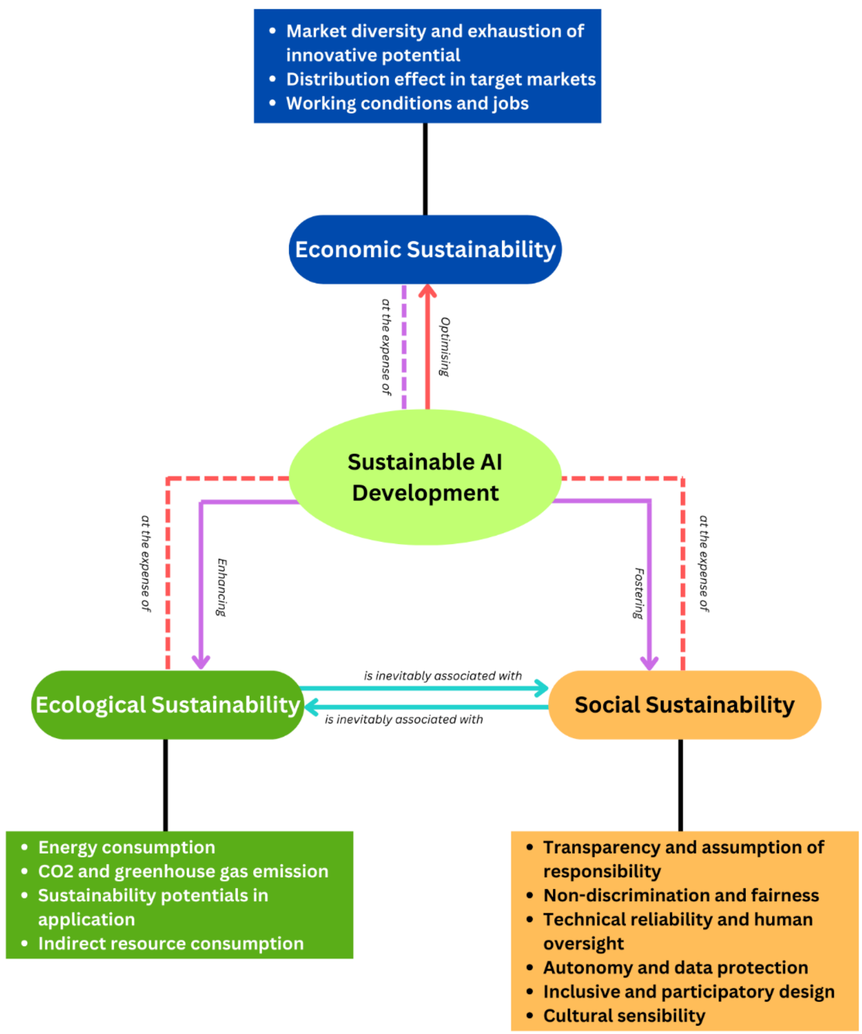
Fig 3.2. Three-Pillar Model of Sustainable AI



Source: Author's formulation based on Barbier (1987) and Rohde et al (2024), 2024

Lastly, drawing from this adopted model, this study further exerts the contemporary theory of sustainable development from Lee and Park (2021) that underscores the considerable potential of a trilemma in realising such sustainable development objectives into a modified theoretical framework (Figure 3.3) as a foundational conceptualised theoretical framework in conducting the research In theory, optimising the three objectives will be at odds each other, making it solely feasible to opt two out of three facets at the same time. For instance, spurring economic growth frequently yield harmful consequences for social equity and environmental preservation. Conversely, prioritising social equity, including social fairness and justice, and enhancing environmental protection may impede economic growth (Lee & Park, 2021).

Figure 3.3. Conceptualised Theoretical Framework



Source: Author's formulation (2025) based on the Three Pillar Model of Sustainable Development (Barbier, 1987), the Sustainability Criteria for AI (Rohde et al., 2024), and the contemporary Theory of Sustainable Development (Lee & Park, 2021)

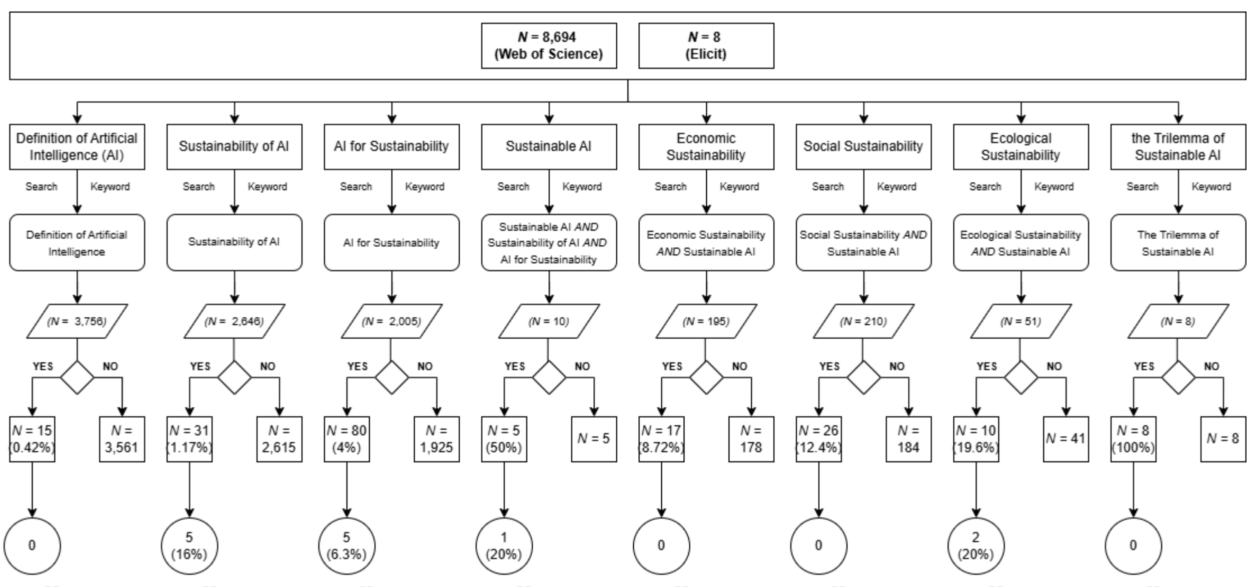
3.2 Data Collection

The data were collected in various ways. *First*, Section 2 on literature review used systematic literature review (SLR) to provide a comprehensive landscape of the published relevant literatures on the topic (Dziopa et al., 2011). *Second*, Section 4 and Section 5 were presented and analysed based on the primary data from semi-structured interviews (Adeoye-Olatunde, et al., 2021) with a varied cohort of participants linked to the topic. *Third*, Section 4 and Section 5 were utilised quantitative dataset from open-source websites pertinent to the research topic, aiming to supplement the qualitative data and arguments (Gerring, 2007).

3.2.1 Systematic Literature Review

Figure 3.4 depicts the process flow of literature review for the study, which retrieved from two main sources, namely (1) Web of Science (N = 8,694) and (2) Elicit (N = 8) with a total article accounted of ∑8,702. The process commenced by determining eight required theoretical definitions linked to the topic, containing of (1) Definition of Artificial Intelligence (AI); (2) Sustainability of AI; (3) AI for Sustainability; (4) Sustainable AI; (5) Economic Sustainability; (6) Social Sustainability; (7) Ecological Sustainability; and (8) the Trilemma of Sustainable AI.

Figure 3.4. Process Flow Diagram of the Conducted Systematic Literature Review (SLR)



Source: Author’s formulation (2025)

Subsequently, pre-selection phase sorted papers predicated on eight pre-determined search keywords aligned with each definition prior filtering, comprising of (1) “Definition of Artificial Intelligence” (*N* = 3,756); (2) “Sustainability of AI” (*N* = 2,646); (3) “AI for Sustainability” (*N* = 2,005); (4) “Sustainable AI *AND* Sustainability of AI *AND* AI for Sustainability” (*N* = 10); (5) “Economic Sustainability *AND* Sustainable AI” (*N* = 195); (6) “Social Sustainability *AND* Sustainable AI” (*N* = 210); (7) “Ecological Sustainability *AND* Sustainable AI” (*N* = 51); and (8) “The Trilemma of Sustainable AI” (*N* = 8).

Among the pre-selected articles, the process continued to distil relevant (YES) and irrelevant (NO) papers screened from the abstract of the papers. The ‘YES’ branch indicates the number of articles that were incorporated into the literature review in Section 2, while the ‘No’ branch were omitted and excluded from the literature review due to the irrelevance of the topic. The quantity of relevant academic articles is varied. For instance, the category of “AI for Sustainability” featured 80 related papers, accounting of 4 per cent out of the total collected publications. In contrast, the definition of “The Trilemma of Sustainable AI’ yielded solely 8 retrieved articles with 100 per cent of relevance, which is reasonable since research topic pertinent to the trilemma of sustainable AI remains measly published and can be grouped into an emerging scholarly issue in academia. Final filtration denoted that relevant academic article with specific locus in Germany remains scarce, accounting for merely two topics, namely (1) “AI for Sustainability” (5 articles); (2) “Sustainability of AI” (5 articles); (3) Ecological sustainability (2 articles); and (4) Sustainable AI (1 article).

Lastly, relevant articles were undergone codification process using Atlas.ti, with the number of times a code has been applied to the article and the number of connections a code has with other codes marked with ‘Groundedness (G)’ and ‘Density (D),’ respectively (Table 3.2). The codification categories comprised six categorisations: (1) Contradicts (><) when the two codes express conflicting ideas; (2) Is a (isa) to mark a subcategory of a code; (3) Is a property of (*) to represent an attribute of the second code; (4) Is associated with (==) to show the relation between two codes without a hierarchical structure; (5) Is cause of (=>) to denote the causes between two codes; (6) Is part of ([]) to epitomise that the first code is a subset of the second one; and (7) Noname to symbolise the unlabelled relationships.

Table 3.2. The Result of Codification from Relevant Articles

Definition	Group Code	Code	∑G	∑D	G (%)	D (%)
Artificial Intelligence (AI)	Definitions of AI	Probabilistic reasoning system	1	3	8	17
		Logic-based systems	3	2	25	11
		Generative system	2	3	17	17
		Data-driven model	2	5	17	28
		Brain-like structures with learning capability	3	2	25	11
		Adaptive agent	1	3	8	17
Sustainability of AI	Definitions of sustainability of AI	Sustainable AI-system	24	1	83	25
		Eco-friendliness AI-system	1	1	3	25
		Green AI	4	2	14	50
	Facets contributing to the sustainability of AI	Multidimensional dimensions	5	0	15	0
		Efficient data training and management	7	2	21	20
		Efficient energy consumption	12	3	35	30
		Sustainable data centres	1	2	3	20
		Less CO2 emissions	9	3	26	30
AI for Sustainability	Definitions of AI for sustainability	Environmental mitigation and conservation	26	3	21	15
		Decision-making enhancement	6	3	5	15
		Environmental monitoring and forecasting	43	4	35	20
		Climate protection	28	4	23	20
		Sustainable business and production optimisation	20	4	16	20
		Carbon capture and storage	1	2	1	10
	Sustainability challenges addressed by AI	Waste management	3	2	8	13
		Urban issues	9	4	23	25
		Water security	12	2	31	13
		Public health	3	3	8	19
		Food security	11	3	28	19
		Poverty alleviation	1	2	3	13
Sustainable AI	Definitions of sustainable AI	Economic sustainability	5	5	36	17
		Social sustainability	3	5	21	17
		Ecological sustainability	3	5	21	17
		Human-centred values	1	5	7	17
		Ethical use of AI	1	5	7	17
		Responsible AI development	1	5	7	17
Economic sustainability	Economic sustainability	Harnessing AI-led innovations	15	6	31	20
		Foster sustainable practices within planetary boundaries	9	3	19	10
		Well-being of society	5	3	10	10

Definition	Group Code	Code	∑G	∑D	G (%)	D (%)
		Sustain economic gains	9	5	19	17
		Cost-effectiveness	6	4	13	13
		Supply chains optimisation	1	4	2	13
		Business innovation	3	5	6	17
Social sustainability	Social sustainability	Harnessing AI-led innovations	25	17	12	14
		Social equity and fairness	13	6	6	5
		Well-being of society	16	12	8	10
		Urban issues	15	9	7	8
		Social cohesion	7	4	3	3
		Decision making enhancement	11	6	5	5
		Ethical standards	8	4	4	3
		Responsible AI development	9	11	4	9
		Human-centred values	4	9	2	8
		Economic sustainability	6	10	3	8
		Eco-friendliness AI-system	2	6	1	5
		Less CO_2 emissions	14	9	7	8
		Ecological sustainability	6	5	3	4
		Environmental monitoring and forecasting	44	5	21	4
		Environmental mitigation and conservation	33	7	15	6
Ecological sustainability	Ecological sustainability	Harnessing AI-led innovations	25	17	11	11
		Environmental mitigation and conservation	33	8	14	5
		Sustainable AI-system	26	9	11	6
		Efficient data training and management	8	6	3	4
		Less CO_2 emissions	14	11	6	7
		Efficient energy consumption	15	6	6	4
		Eco-friendliness AI-system	2	9	1	6
		Climate protection	33	10	14	6
		Green AI	6	9	3	6
		Responsible AI development	9	13	4	8
		Human-centred values	4	9	2	6
		Ethical use of AI	2	6	1	4
		Social equity and fairness	13	6	6	4
		Well-being of society	16	14	7	9
		Urban issues	15	9	6	6
		Public health	5	4	2	3
		Sustain economic gains	10	8	4	5
The trilemma of sustainable AI*	N/A	N/A	N/A	N/A	N/A	N/A

Source: Author’s formulation (2025)

3.2.2 Semi-structured Interview

The second way of collecting the data was undertaken through a collection of semi-structured interviews to provide a balanced structure with flexibility, allowing me to dive deeper into interviewees' insights while maintaining a systematic and adaptable approach with potential interviewees (Adeoye-Olatunde et al., 2021). These purposely targeted a varied cohort of participants, encompassing experts from (1) the German public sector; (2) civil society organisations; (3) international organisations; (4) academia; and (5) industry/startups. Interviewees were selected predicated on pre-determined criteria as shown in Table 3.3 for each target group along with their specific key roles.

Table 3.3. Selection Criteria for Interviewees

No.	Target Group	Selection Criteria	Key Roles
1.	German Public Sector*	The interviews are conducted with key personnel involved in either operational or strategic roles within public sector institutions, whether at the Federal Government (*Bundesregierung*) or State Government (*Landesregierung*) level. The focus is on their contribution on policy making and governance linked to the development of sustainable artificial intelligence (AI). The interviews target public officials engaged in AI governance, AI-related policy development, sustainable AI or technology initiatives, and sustainable digital and technological transformation within public sector institutions. Specifically, the targeted interviewees work in government agencies in the Federal or State government that are directly involved in shaping and implementing AI strategies at the national or regional level.	• Executive leadership: (1) Department Head or (2) Chief Officer related to AI, sustainable technology, or digital transformation • Policy and administration: (1) Senior civil servants; (2) legal advisors; (3) AI policy officers; (4) AI policy advisor shaping AI governance and sustainability regulations • AI Strategy and Innovation Analyst: AI policy analyst • Project Management: (1) Project Officer and (2) Program Manager related to the implementation of AI policy into government services and programs including economic, social, and environmental impact.
2.	Civil Society Organisation	The interviews were conducted with key experts and researchers from civil society organisations (CSOs) engaged in AI governance, sustainability, ethics, and digital rights advocacy. The focus is on their contributions to policy discussions, public engagement, and research related to sustainable AI development, responsible AI deployment, and the societal impact of AI technologies. The interviews target professionals working in think tanks, advocacy	• Policy and Regulatory Experts: (1) Senior Policy Analysts, (2) AI Governance Specialists, (3) Digital Economy and Innovation Experts focusing on AI regulatory frameworks. • AI and Sustainability Analysts: (1) AI and

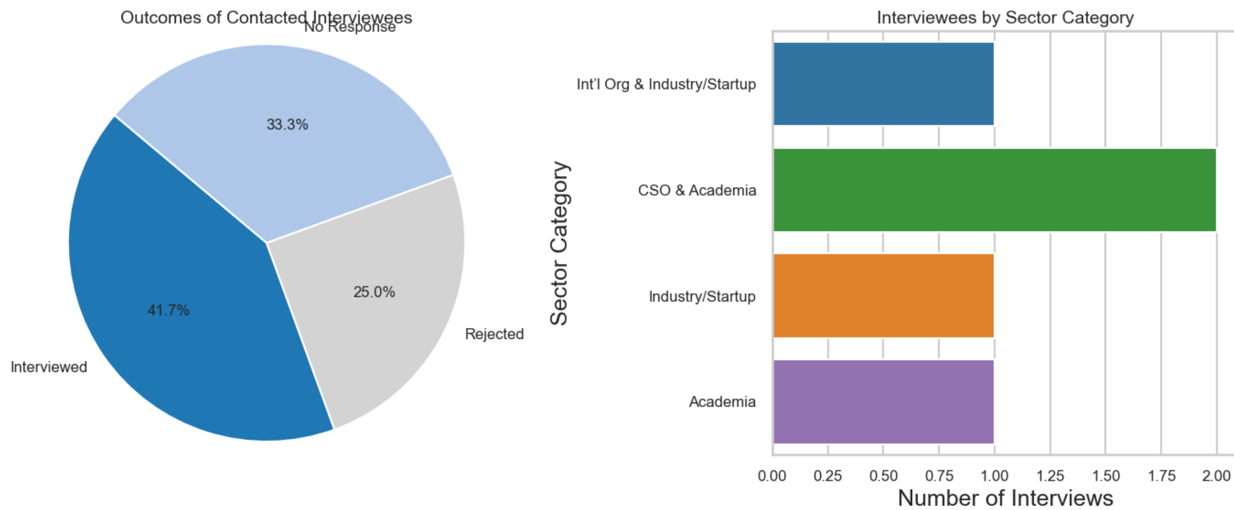
No.	Target Group	Selection Criteria	Key Roles
		groups, NGOs, and independent research institutions that influence AI policies, ethical guidelines, and sustainability frameworks at national and international levels.	Environmental Policy Experts, (2) Sustainable AI Researchers, (3) AI and Climate Policy Advisors.
3.	Industry and Startups	The interviews were conducted with key personnel involved in either operational or strategic roles within private sector companies, including startups and established enterprises developing or integrating artificial intelligence (AI) solutions, in Germany. The focus is on their contributions to AI innovation, governance, and the advancement of sustainable AI in industry. The interviews target professionals engaged in AI development, ethical AI implementation, sustainability-driven AI solutions, and digital transformation within the private sector. Particularly, the targeted interviewees work in AI-focused startups, technology firms, and enterprises that are actively shaping and deploying AI strategies for sustainable economic, social, and environmental impact at the national level.	• Executive Leadership: (1) CEO, (2) CTO, (3) Chief AI Officer, or (4) Chief Sustainability Officer driving AI and digital transformation strategies. • AI Development and Strategy: (1) AI Engineers, (2) AI Researchers, (3) AI Product Managers, and (4) Innovation Leads working on AI-driven sustainability initiatives. • Regulatory and Ethics Advisory: (1) AI Ethics Officers, (2) Compliance Managers, (3) Policy Analysts focusing on AI governance and responsible AI deployment. • Sustainability & Impact Strategy: (1) ESG (Environmental, Social, and Governance) Officers and (2) AI and Sustainability Consultants. • Project and Program Management: (1) AI Project Managers and (2) Business Development Leads overseeing AI adoption and integration into industry solutions.
4.	International Organisation	The interviews were conducted with key policy analysts and experts from international organisations engaged in AI governance, sustainability, regulatory frameworks. The focus is on their contributions to policy development, strategic recommendations, and regulatory guidance related to sustainable AI, responsible AI deployment, and the societal and economic impact of AI. The interviews target professionals working in global institutions such as the OECD, UN agencies, World Economic Forum, and other international think tanks that influence AI policies, governance frameworks, and	• Policy and Regulatory Experts: (1) Senior Policy Analysts, (2) AI Governance Specialists, (3) Digital Economy and Innovation Experts focusing on AI regulatory frameworks. • AI and Sustainability Analysts: (1) AI and Environmental Policy Experts, (2) Sustainable AI

No.	Target Group	Selection Criteria	Key Roles
		sustainability initiatives across multiple countries, with a specific interest in Germany's AI landscape.	Researchers, (3) AI and Climate Policy Advisors. • International AI Strategy and Implementation Specialists: (1) AI in Public Sector Experts, (3) AI and Economic Development Specialists.
5.	Academia	The interviews will be conducted with key academic professionals engaged in research, teaching, and policy discussions related to Artificial Intelligence (AI) and sustainability. The focus is on their academic contributions to AI governance, sustainable AI development, and ethical AI implementation in both theoretical and applied contexts. The interviews target researchers and scholars involved in AI ethics, AI policy development, and sustainable AI innovation within universities and research institutions in Germany. In particular, the targeted interviewees are academics and researchers working on AI-related sustainability challenges, governance frameworks, and interdisciplinary AI applications that shape policies, industry practices, and socio-economic impact.	• Professors and Senior Experts: (1) Professors, (2) Associate Professors, and (3) Senior Researchers specialising in AI governance, ethics, and sustainable AI innovation. • Research Associates: (1) AI Researchers, (2) Sustainability & AI Policy Experts, (3) Postdoctoral Researchers focusing on AI and sustainability. • PhD Students & Early-Career Researchers: (1) PhD Candidates researching AI ethics, governance, or sustainable AI applications, (2) Research Assistants contributing to AI and sustainability projects. • Interdisciplinary AI Scholars: Experts from computer science, law, public policy, environmental studies, and social sciences examining AI's role in economic, social, and environmental sustainability.

Source: Author's formulation (2025) *Interviewees for the German Public Sector were not successfully conducted due to the absence of responses from the contacted people.

Of a total of 12 contacted interviewees, 5 were successfully interviewed (42%), while 4 persons did not provide a response (33%), and 3 people rejected the invitation for an interview. Those who did not respond to the invitations were dominated by targeted public sector interviewees, whereas those who rejected the interview requests stated their concerns about secretive government or company material and information that may not be publicly informed. Among the 5 completed interviewees, 2 people represented CSO and academia (40%), and 1 person in each sector of international organisations and startups, industry and startups, and academia. (Figure 3.5).

Figure 3.5. Stats of the Interviewees

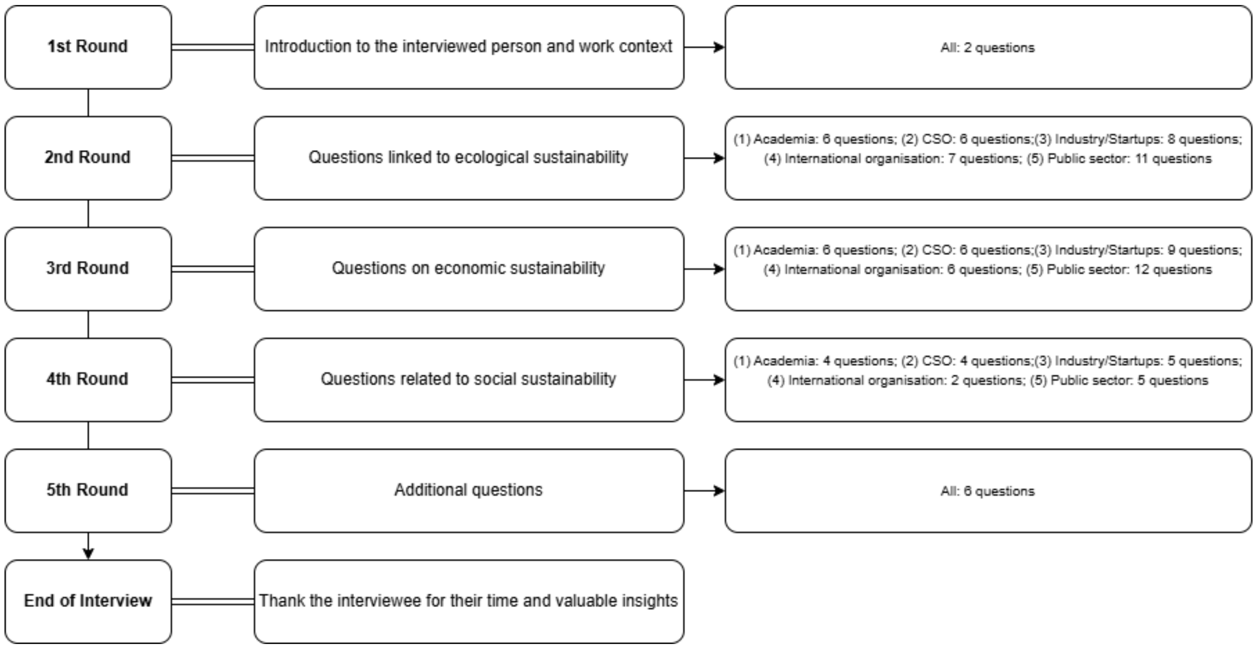


Source: Author's formulation (2024).

The interview process utilised digital tools, including Google Meets and Zoom, to conduct interviews with all the respondents. I conducted a total of five rounds of interviews, each with a varied number of questions tailored to different groups of interviewees. The first round contains an introduction to the interviewed person and the work context of the thesis. The second session was dedicated to specific questions of ecological sustainability. In this context, ecological sustainability refers to the degree of practising responsible resource management to minimise energy use, reduce emission and waste, and ensure long-term environmental preservation (Bolte et al., 2022; Rohde et al., 2024).

Subsequently, I enquired about questions linked to economic sustainability. In particular, this term is related to market fairness and resilience, innovation, equitable distribution, and quality for sustainable economic growth (Bolte et al., 2022; Rohde et al., 2024). The fourth session asked enquiries on social sustainability, including promoting fairness, inclusivity, and accountability while safeguarding the public's or user's personal right (Bolte et al., 2022; Rohde et al., 2024). Lastly, I asked an additional question before ending the interview process. These questions include any key challenges or opportunities that have not been discussed, ways forward on German AI-related policies, interest in reading the final submitted thesis, and recommendations of interviewees (Figure 3.6).

Figure 3.6. Questions of the interview



Source: Author's formulation (2024).

3.2.3 Complementary quantitative dataset

Quantitative data were collected through relevant open-sourced websites, including (1) OECD.AI; (2) the Joint Research Centre data catalogue; (3) KI-Strategie-Deutschland; (4) the 2025 Stanford AI Index; (5) Eurostat; (6) Lernende Systeme; and (7) Statista.

3.3 Data Analysis

3.3.1 Analysing Semi-Structured Interview Results

The results of semi-structured interviews were transcribed utilising TurboScribe and codified using Atlas.ti. The number of times a code has been applied to the article marked with 'Groundedness (G)' (Table 3.4). The codification categories comprised six categorisations: (1) Contradicts (><) when the two codes express conflicting ideas; (2) Is a (isa) to mark a subcategory of a code; (3) Is a property of (*) to represent an attribute of the second code; (4) Is associated with (==) to show the relation between two codes without a hierarchical structure; (5) Is cause of (=>) to denote the causes between two codes; (6) Is part of ([]) to epitomise that the first code is a subset of the second one; and (7) Noname to symbolise the unlabelled relationships. Subsequently, the codes were analysed using network analysis in Atlas.ti to yield analytical figures to grasp the relation between codes. (Table 3.4).

Table 3.4. The Result of Codification from Interviews

No.	Code	∑G	G (%)
1.	AI for sustainability and Sustainability of AI	1	2.08
2.	AI sovereignty	1	2.08
3.	Algorithmic discrimination	2	4.17
4.	Concentrated market power	3	6.25
5.	Feasibility of reusable heat technology	1	2.08
6.	High demand of air-based cooling system	1	2.08
7.	Human-centric AI	2	4.17
8.	Inefficient regulatory processes	3	6.25
9.	Innovation at odds with regulation	1	2.08
10.	Lack of transferability	2	4.17
11.	Less cooperation between industry and the government	2	4.17
12.	Less inclusive regulatory process	1	2.08
13.	Less public involvement	1	2.08
14.	Long permitting process	1	2.08
15.	Monitoring on carbon emission	2	4.17
16.	Promoting digital sovereignty	1	2.08
17.	Regulation can promote innovation	2	4.17
18.	Regulation can promote responsible AI	1	2.08
19.	Regulatory hurdles	5	10.42
20.	Shortage of highly skilled workers	1	2.08
21.	Silo in AI governance	3	6.25
22.	Social cohesion	2	4.17
23.	Sustainability of AI systems	2	4.17
24.	Sustainable AI as a multi-dimensional concept	6	12.5
25.	Transparency from AI industry	1	2.08

Source: Author's formulation (2025)

3.3.2 Analysing Complementary Datasets

The collected open-sourced datasets were extracted into Excel files, then analysed and visualised using R and Python. Some figures were produced utilising R (i.e., the figure on VC investment), while the others were using Python (i.e., the figure on Germany maps). This different approach was undertaken based on the specialisation of each programming language to yield proper figures; for instance, Python was selected due to its specialisation to produce better map figures using the geopandas feature compared to R.

3.4 Research Limitation

This research possesses some limitations. *First*, arguments based on the interview findings may exhibit biases stemming from the subjectivity of the participants. *Second,* less interviewees from the German public sector. *Third*, due to the current absence of granular framework for assessing sustainable AI approach, the analysis results may lack nuanced rationale. *Fourth*, the findings of this research cannot be generalised as universal evidence, as they pertain exclusively to Germany, and evidence from other nations may differ.

4. RESULTS

4.1 Existing challenges encountered by Germany in promoting Sustainable AI practices

This section contains six persistent obstacles that may hinder the escalation of current positive developments regarding advancing sustainable AI in the country, encompassing (1) divergence in semantics definition of the term “sustainable AI”; (2) regulatory hurdles; (3) silo in AI governance; (4) potential harmful consequences on the environment; (5) critical social concerns; (6) lag in AI adoption across enterprises; (7) limited AI adoption across the public sector; (8) market concentration in sustainable AI projects; (9) shortage of highly skilled workers; and (10) limited transferability across SMEs.

4.1.1 Divergence in semantics definition of the term “Sustainable AI”

The term “sustainable AI” remains divergent amongst AI experts globally, since this particular semantics remains considered an emerging ethical debate in the realms of AI ethics, notably environmental ethics. Nonetheless, a semantics definition coined by Prof. Amy von Weinsberg has become a guide for many, including one of the following interviewees:

> *“Well, I would stick to the basic of what Amy von Weinsberg in her paper. She distinguished between the term sustainable AI to encompass the two perspectives, AI for sustainability and then sustainability of AI. I don't really have to mix the two approaches. And we always had this kind of working definition in our project. It's the same project that we said sustainable AI has the three dimensions, the three pillars of sustainability, has a social, ecological and an economic sustainability aspect to it.”* (Interviewee 1, with a background of Civil Society Organisation and Academia).

Interviewee 1 interpreted the term “sustainable AI” as an umbrella that contains two facets, namely (1) AI for sustainability and (2) sustainability of AI, and used these two aspects in the previous flagship project of “SustainAI”. This concept has three derivative pillars of sustainability, encompassing (1) social, (2) ecological, and (3) economic sustainability that are entangled with each other. Conversely, Interviewee 2 debunked the common understanding of sustainable AI with its two essential pillars, AI for sustainability and sustainability of AI, arguing that dichotomising such a definition would only spawn imbalance in grasping the term as a comprehensive concept as stated below.

[…] I would say it's a wrong dichotomy. And that happens very often in the discussion. I mean, people like balance, and there's the negative side and the positive side, but the way people frame it is that the negative side is very, as you said, it's very, very much focused on the infrastructure. And the positive side is very much focused on the applications. And it's definitely not as black and white. It's not like, yes, AI takes a lot of energy, but it can do very, very sustainable things. It's much more complex than that […]" (Interviewee 2, with a background as an AI expert at an International Organisation).

Interviewee 2 emphasised the importance of interpreting the term "sustainable AI" in a comprehensive perspective, avoiding oversimplifying it and preserving its potential to produce sustainable outcomes and solutions. Whereas Interviewee 3 underlined two intertwined aspects, namely social, ecological and economic impacts, in particular, and noted the need to perceive sustainable AI as a comprehensive concept embedded throughout the life cycle of the AI systems.

"[…] And this is like this AI for sustainability because yes, we can use those systems for, I don't know, climate modelling or I don't know, aspects which are related to sustainability. But there are many, many, many other applications which are not related to sustainability at all. And that's why for me, and that's also the perspective we developed within this project, when we really want to have an overarching sustainability perspective, it's about looking at the whole AI lifecycle and also not only looking at the application area, but also like how is the whole system designed and like what materials are used for the hardware in the data centres and stuff. So it's like it's much more than only we like to use this AI to tackle climate change or I don't know. […]" (Interviewee 3, with a background of Civil Society Organisation and Academia).

Furthermore, Interviewee 2 emphasised the imperative of taking into account any potential harmful consequences on social cohesion when conceptualising the framework of "sustainable AI". This means that the term "sustainability" should not be defined in a narrow scope of the sustainability of AI, instead broadening the sustainability approach within the planetary boundaries.

"[…] So, we always said sustainable AI should not endanger social cohesion. It should stay within the planetary boundaries. And it should not aggravate economic concentration. So, this is a broad sustainability approach and just very much focused on the sustainability of AI." (Interviewee 3, with a background of Civil Society Organisation and Academia).

4.1.2 Regulatory hurdles

The enactment of the Energy Efficiency Act (*Energieeffizienzgesetz*), which aimed to comply with the EU Energy Efficiency Directive, has faced significant criticism for being excessively stringent and impractical from the perspective of businesses. Interviewee 4 and Interviewee 2 underscored the disparity of the regulatory framework between Germany and its European counterparts, underlining that stricter enforcement of such directives has indirectly imposed an extra burden on the data centre sector in the country. Another notable deficiency in the Energy Efficiency Act is regarding the impracticality of imposing stringent energy reuse targets without regard for contextual feasibility. For instance, Interviewee 4 further outlined that there is an issue ofeat off-take, which pertains to the ability of data centres to utilise waste heat, and it was emphasised as dependent on local infrastructure, which is not generally available in the country at the moment.

> *"And also, now with the new energy efficiency law, there's also some regulatory burdens in Germany that are much higher than in other European countries. Because, I don't know if you're into the topic, but we're having the energy efficiency directive on a European level. So, there are, in theory, should be a low playing field. But Germany applied this directive very strictly, implemented a lot of regulation that went way beyond what the directive proposes. So that's also an increasingly negative factor on the data centre market because the regulation that was implemented is very strict and also not really, what's the word for that? It's not really viable in practise because, for example, one of the things they proposed is that new data centres, which start operating after 2026, have to have an energy reuse factor of 10, 15, 20 percent over three years. No matter the outside circumstances, network or whatever. And that's not something that a data centre operator can, that's right, a data centre operator can't. They need to be reused. They have to be low and cost neutral. But if there's no offtake for several reasons, for example, no heating district, network, or maybe it's not economically feasible, that's often the reason. Because, yeah, the heat from the data centre is often only about 30 degrees higher than what the heat power. And maybe it's not economically feasible anymore for the heat operator. So, for example, the data centre operator can't do that. So, yeah, that's why the regulation is a big problem for the industry."* (Interviewee 4, with a background as an data centre policy expert at a national digital association)

> *"But, yeah, with the energy efficiency law, the industry is very unhappy with how it was consulted, how the law was implemented now in a good form. So, there's a lot of improvements that can be made on that front, because, as I already mentioned earlier, from the perspective of the industry, the law is not very practical and applicable right now. And from our perspective, from the perspective of the data centre industry, the industry's voice wasn't heard enough, especially in the early phases of the law."* (Interviewee 4, with a background as an AI expert at an International Organisation).

Furthermore, Interviewee 4 revealed the distinguished approach of such a regulatory development process between Germany and the European Union, highlighting that there was less inclusivity during the legislation process, notably in gathering perspectives from the industrial sector.

> *"There were some improvements made in the policy process, but especially at the beginning, the law that came out of the ministry was very unproductive. It was much worse than it is now. But, yeah, the industry's voice is not heard enough. To be honest, on a European level, it's very different. There, we have seen a lot of consultation with the industry."* (Interviewee 4, with a background as an data centre policy expert at a national digital association).

Interviewee 4 and Interviewee 2 also shed light on the permitting issue of data centres that hampers the industry in the country from scaling up AI and high-performance computing requirements in practice. This phenomenon is considered a bottleneck that may impede Germany in vying with other European and global AI key players to spur exponential innovation growth and advancement in AI.

> *"We are also seeing is that the permitting process takes very long in Germany, also when compared to other European countries, especially in such a fast-evolving industry as a data centre industry. We're seeing AI evolving very fast, so demands rising very fast for data centre capacity. And in Germany, it's very hard to meet this demand in time because of the long permitting process."* (Interviewee 4, with a background as an data centre policy expert at a national digital association)

> *"[…] But of course, Germany being Germany, they probably approach it in a way of doing a lot of legislation. There's the Energy Efficiency Act that mandates certain like percentages*

> *of access that's being repurposed. And like that might eventually slow down world data centres, for example, because companies are just going to go elsewhere."* (Interviewee 2, with a background as an AI expert at an International Organisation).

On the contrary, Interviewee 1 provided a different perspective, countering the argument of regulation often at odds with innovation. The following statement highlighted that instead of hampering innovation, legislation could actually promote more continuous innovation trajectories, as reflected from good practice from the United States-centric approach.

> *"[...] I can just say that this whole narrative of regulation impeding innovation is always there and it's very unsubstantiated. One could equally argue that regulation in this sort fosters innovation and DeepSeek might be an example of that, right? We don't have to follow the US approach of scaling, compute, scaling, model architecture, scaling, data set size. This is not the only way to innovation. So, I think if we truly want to find a European approach, we don't have to mirror what is done in America and the US. So, I feel like this whole narrative is very unsubstantiated. It is not legitimised in any way."* (Interviewee 1, with a background in Civil Society Organisation and Academia).

4.1.3 Silo in AI governance

Silo in the German AI ecosystem is considered a primary caveat, as reflected in the absence of integrated coordination among relevant governmental actors and federal states, leading to fragmented governance practices that impede coherent implementation and integration of AI initiatives across the country's ministries and states. This is in contrast to other global key AI players, such as the United Kingdom, which provided a dedicated governmental institution directing national AI strategy and initiatives, as stated by Interviewee 2 below.

> *"I think that goes back to the federal and state system of Germany. So already on the state level, you don't have a central agency or ministry that is doing even digital, not AI, but like digital policy. So in the UK, for instance, you have an AI office, and all they do is AI. And that's where all the AI initiatives come together. In Germany, you have the BNBK, so the Ministry for the Economy does something. And you have the Digital and Infrastructure Ministry that does something. And the Ministry for the Interior is responsible for digital*

> *initiatives on the bureaucracy."* (Interviewee 2, with a background as an AI expert at an International Organisation).

This divergence of responsibilities is reflected in the distribution of AI initiatives in a sectoral approach, resulting in diverse AI projects conducted by different ministries without acknowledging each project among the counterpart ministries, resulting in a potential overlapping of related initiatives linked to AI in the country.

> *"[…] Then you have every other ministry, the Ministry for Agriculture does AI for agriculture. So you have already only on state level, a lot of different ministries who do a lot of different initiatives, and they're not necessarily aligned or coordinated, because there's no central place where they are coordinated. So in many ways, our report was the first time that many of these initiatives heard about each other, because they suddenly sat in the same room, and then somebody was like, oh, we're also doing that. So you end up with like, two ministries doing basically the same thing. But they had never heard about each other. So that's already a big problem."* (Interviewee 2, with a background as an AI expert at an International Organisation)."

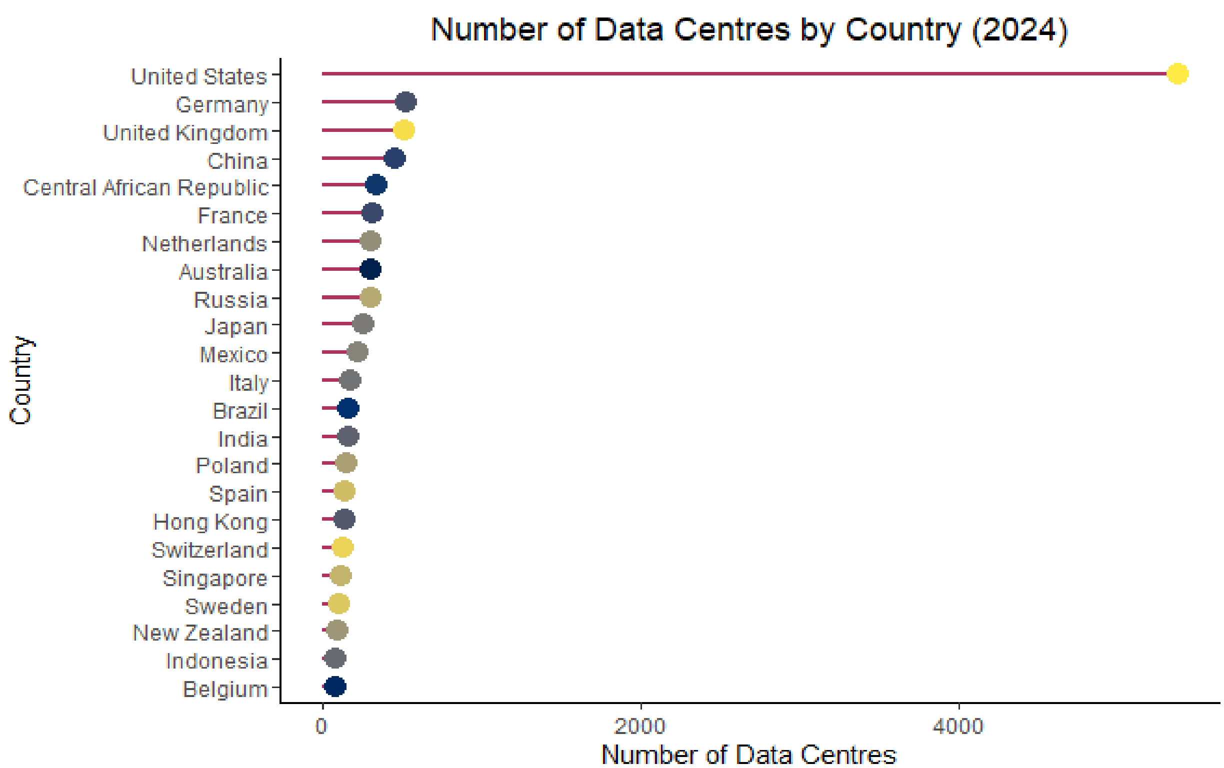
Further, the German federal system aggravates the persisting fragmented AI governance ecosystem, as each *Bundesland* has the authority to pursue its own AI agenda. Not to mention, the absence of coherent coordination between state and federal levels intensifies this critical impediment.

> *"And then the next problem is the kind of the federal structure of Germany, so with the Bundesländer. And then each Bundesland has its own, some have a private AI initiative, some have a state level AI initiative, some don't have an AI initiative. And then the different, so Bavaria, for example, has a digital ministry. But that's not common in many other Bundesländer. So again, on state level, a lot of different actors, a lot of different initiatives, and they also don't communicate with the federal level. So what you end up with is a big cluster of a lot of cool initiatives that are not necessarily coordinated. And sometimes you don't know that someone in the next Bundesland is doing the same thing."* (Interviewee 2, with a background as an AI expert at International Organisation).

4.1.4 Potential harmful consequences on the environment

The data centre primarily contributes to the side effects of harnessing AI-led technologies because it plays a crucial role in supplying the energy needed for intensive data training. As of 2024, Germany ranks second only to the United States in terms of the number of data centres, implying its central position in advancing and leveraging data centres for AI and supercomputing, exceeding other key players, including the United Kingdom, China and France (Figure 4.1). The growth of the data centre industry in Germany is primarily due to digitalisation and AI integration in various sectors in the country.

Figure 4.1. Number of data centres in Germany



Source: Author's formulation (2025) extracted from Statista (2024).

Amidst the exponential energy consumption of data centres, Interviewee 4 explained that efficiency in using the energy is also growing simultaneously, noting that the rise in energy use is commensurate with the rapid expansion of data centres propelled by industry.

> *"Also, better usage of waste heat, because the temperature is higher, compared to distributed heating, for example. So, that is a very important thing. Also, generally, increasing the heat reuse of data centres, because what we are seeing right now in Germany is there is a high increase of our projects where waste heat is being reused, but it is still pretty low, especially for big projects. So, you're correct that obviously with the growth of the sector and the growing digitalisation, AI, the energy consumption of the data centre industry is increasing. But it has to be added to that that efficiency is also increasing, so the growth of energy demand is rising slower than the growth of the sector in general."* (Interviewee 4, with a background as an data centre policy expert at a national digital association).

Another notable issue is linked to the imperative of shifting towards renewable energy to supply the raising demand of electricity that becomes the heart of data centres. This action becomes salient to reduce the amount of carbon footprints at the same time, as stated by Interviewee 4 below.

> *"[...] And one of the most important things that has to be done to meet this demand and sustainable is driving forward the energy transition towards more renewable energies and sustainable energy production because more than 80% of the emissions by data centres in Germany is actually from the electricity they are consuming and so forth. That is the biggest thing that can be done to reduce the carbon footprint of data centres, so that is a very important thing."* (Interviewee 4, with a background as an data centre policy expert at a national digital association).

Further, Interviewee 4 underlined that power purchase agreements (PPAs) are increasingly exerted by large private industries to guarantee that their data centres operate utilising renewable energy. These kinds of industries, buoyed by their financial strength, play key roles to drive sector-wide energy transition.

> *"Almost all large data centre operators are already running on renewable energy, by PPAs, by other contracts. [...] they are really investing a lot of money in that and trying to make an energy transition for everyone."* (Interviewee 4, with a background as an data centre policy expert at a national digital association).

Another challenge lies in the reuse of waste heat that remains underdeveloped in Germany, notably in data centre industries. While there have been notable developments in recent years through projects related to the reutilisation of data centre waste heat, the outcome is still considered minimal.

> *"We are seeing right now in Germany […] a high increase of our projects where waste hear is being reused, but it is still pretty low, especially for big projects."* (Interviewee 4, with a background as an data centre policy expert at a national digital association).

Economic feasibility is considered as the hiccup, notably for operators of district heating networks. This is due to the need for yielding cost-competitive implementation to effectively scale the reuse of waste heat, similar to fossil-based heat sources.

> *"It has to be more economically feasible […] for the heating network, operators, also for the end customers, so it is a competitive source of heat, compared also to fossil heating."* (Interviewee 4, with a background as an data centre policy expert at a national digital association)

4.1.5 Emerging social concerns

Most of the Germans (60 per cent) claim to understand AI as a technology (above France and below Hungary, with scores of 61 per cent and 75 per cent, respectively); both trust and excitement are limited, with solely 39 per cent expressing excitement over AI products and merely 43 per cent possessing trust in AI companies to safeguard their private data. The majority of Germans believe that AI shows bias, with only 48 per cent of respondents trusting AI to not perform bias, compared to Hungary (64 per cent) and Italy (61 per cent). However, most Germans (59 per cent) are optimistic that AI will impact their lives in the next 3 to 5 years, although this percentage is lower than in other countries, such as Hungary (66 per cent) and Ireland (64 per cent). (Table 4.1)

Table 4.1. Public perceptions and trust on AI (2025)

Statement	BE (%)	FR (%)	DE (%)	HU (%)	IE (%)	IT (%)	NL (%)	PL (%)	ES (%)	SE (%)	CH (%)
Products and services using artificial intelligence have profoundly changed my daily life in the past 3-5 years	34	35	39	37	42	40	32	41	43	31	38
Products and services using artificial intelligence make me excited	33	39	46	47	40	49	40	44	45	36	42
Products and services using artificial intelligence will profoundly change my daily life in the next 3-5 years	61	57	59	64	59	60	63	56	59	52	55
I have a good understanding of what artificial intelligence is	65	61	60	75	66	51	70	67	65	65	57
I trust that companies use artificial intelligence will protect my personal data	40	35	43	64	42	58	44	45	48	35	43
I trust that companies use artificial intelligence to not discriminate or show bias towards any group of people	37	41	48	64	42	61	38	53	52	33	43

Source : Author's formulation extracted from Stanfrod's AI Index 2025 (2025).

Note: % represents the weight of survey's participants that agreed with the statement. The data is extracted from the Stanford AI Index 2025.

Table 4.2. Public Opinions on the potential of AI to improve life by country (2025)

Statement	BE (%)	FR (%)	DE (%)	HU (%)	IE (%)	IT (%)	NL (%)	PL (%)	ES (%)	SE (%)	CH (%)
My entertainment options	39	33	43	39	52	44	42	37	48	39	40
My health	34	39	27	31	35	38	25	24	33	21	30
My job	26	33	27	24	33	32	27	21	28	32	29
The amount of time it takes me to get things done	49	50	41	55	47	47	53	48	48	41	43
The economy in my country	23	29	31	27	31	31	24	24	33	21	32
The job market	17	27	22	25	25	25	21	21	17	18	25

Source : Author's formulation extracted from Stanfrod's AI Index 2025 (2025).

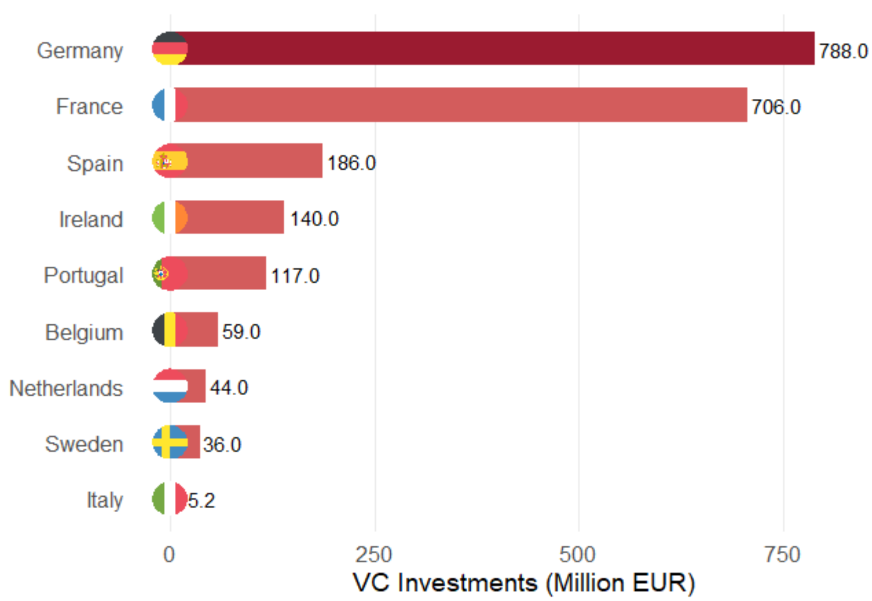
Note: % represents the weight of survey's participants that agreed with the statement. The data is extracted from the Stanford AI Index 2025.

According to the same index's dataset, Germany (41 per cent) ranks lower compared to the global average (55 per cent) and Hungary (55 per cent) in perceiving AI as a tool to expedite task completion. In terms of well-being, solely 27 per cent of German respondents see AI providing a positive outcome for their health, scoring below the global average of 38 per cent and trailing behind countries like France (39 per cent) and Italy (35 per cent), while exceeding Sweden (21 per cent). Another measured indicator is employment-related opinions, with only 27 per cent of Germans expecting that AI would improve the quality of their work and 22 per cent believing in a positive effect on the labour market. (Table 4.2).

4.1.6 Lag in AI adoption across enterprises

Germany showcases strength in alluring VC investments in AI compute and topped other EU countries by securing €788 million in 2024, higher than France (€706 million) and considerably surpassing Spain (€186 million), Ireland (€140 million), Portugal (€117 million), Belgium (€59 million), Sweden (€36 million), the Netherlands (€44 million), and Italy (€5.2 million). This also reveals a stark concentration of VC investments in AI compute in the EU with Germany and France dominating the continent. (Figure 4.2).

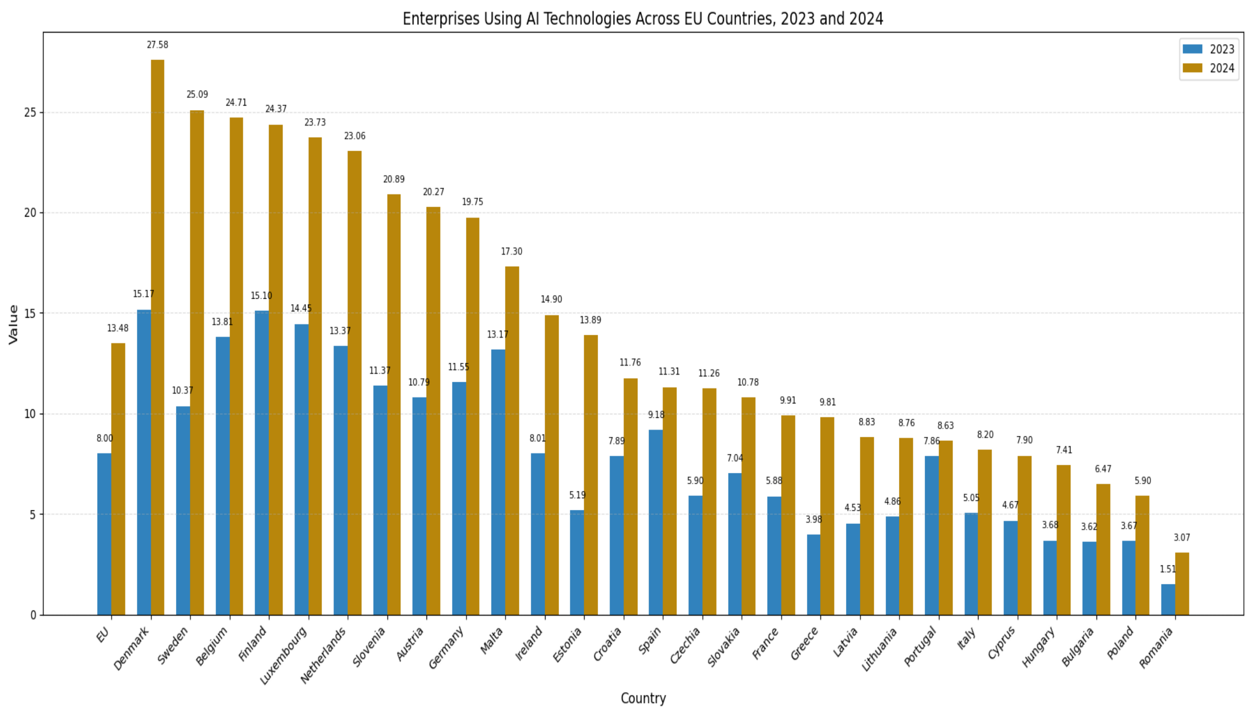
Figure 4.2. VC Investments in AI compute by country (2024)



Source: Author's formulation (2025), extracted from OECD.AI

In contrast, the adoption rate of AI among enterprises in Germany implies a moderate performance. In 2023, 11.55 percent of enterprises in Germany reported having used AI, increasing to 19.75 percent in 2024, a rise of 8.2 percent. While this surge indicates a positive improvement, Germany remains behind other frontrunners such as Denmark (15.17 per cent in 2023 and 27.58 per cent in 2024, or 12.41 per cent of the rise) and Sweden (10.37 per cent in 2023 and 25.09 per cent in 2024, or 14.72 per cent of the rise). Some other EU counterparts, including Belgium, Finland, and the Netherlands, also surpassed Germany's growth, leaving Germany solely exceeding several Eastern and Southern European countries like Italy, Poland, and Romania, who have a relatively low adoption. (Figure 4.3).

Figure 4.3. Enterprises using AI technologies across EU countries (2023 and 2024)

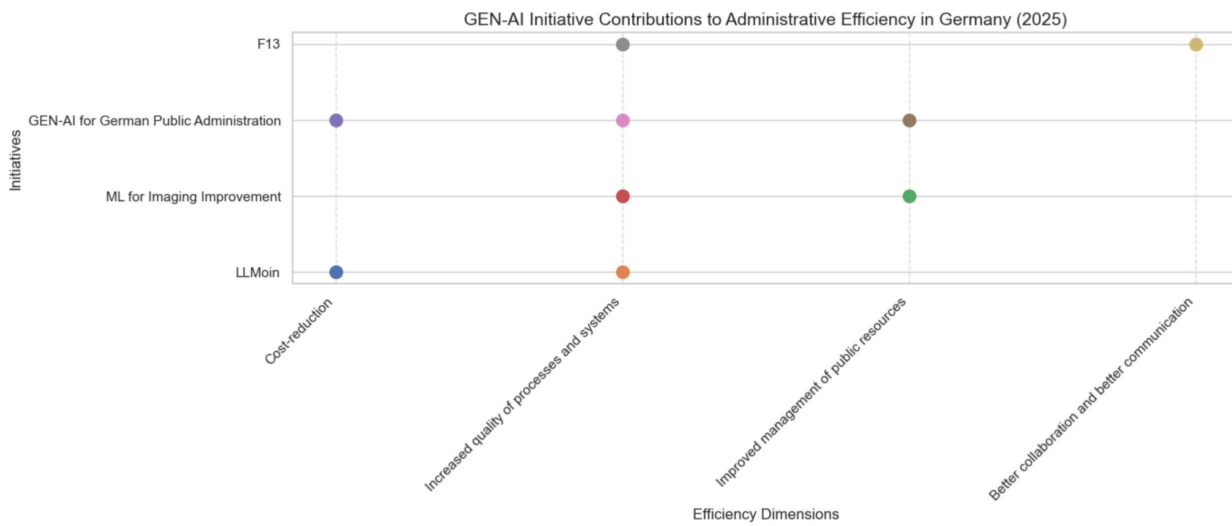


Source: Author's formulation, extracted from Eurostat (2025)

4.1.7 Limited AI adoption across the public sector

The state of AI implementation in the public sector is relatively at its infancy and is predominated by generative AI (Gen-AI)-led innovations with notable initiatives, such as F13, Gen-AI for German Public Administration, ML for imaging improvement, and LLMoin. These projects primarily aim to increase the quality of internal processes and systems within the government's activities while still leaving room for more utilisation to promote cost reduction, management of public resources, and betterment in collaboration and communication across government sectors. (Figure 4.4 and Table 4.3).

Figure 4.4. AI in the public sector



Source: Author's formulation, compiled from JRT publications repository (2025)

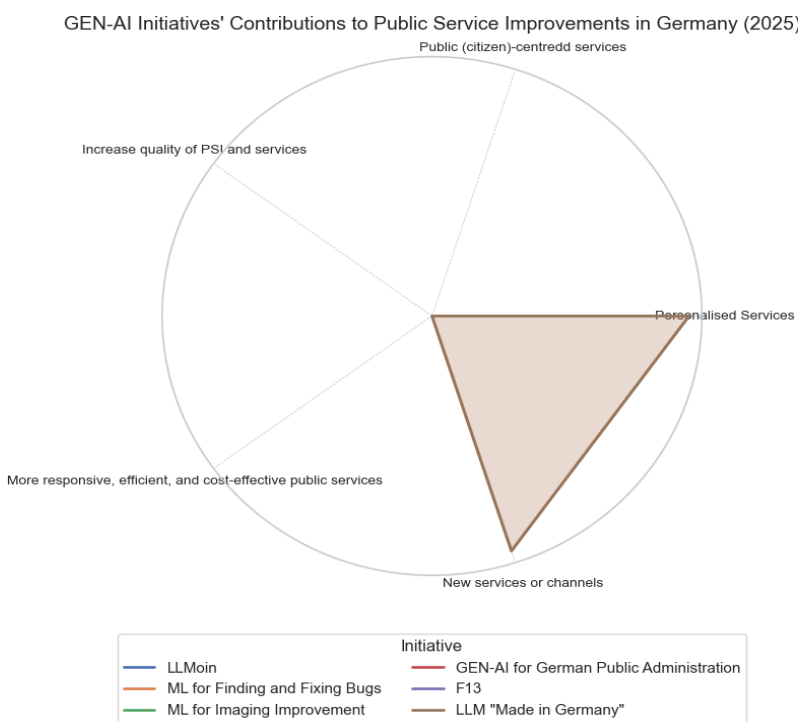
Table 4.3. Initiatives linked to AI in the German Public Sector

Name	Scope	Responsible organisation	Year of Launch	Governmental function	Status	Process type
LLMoin	Local	City of Hamburg	2024	General public services	Pilot	Internal management
ML for Finding and Fixing Bugs	National	University of Stuttgart	2024	Economic affairs	Pilot	Analysis, monitoring and regulatory research
ML for imaging improvement	National	Bundesamt für Ausrüstung, Informationstechnik	2022	Defence	In development	Internal management

Name	Scope	Responsible organisation	Year of Launch	Governmental function	Status	Process type
		und Nutzung der Bundeswehr				
Gen-AI for German Public Administration	National	Aleph Alpha	2023	General public services	Pilot	Internal management
F13	Regional	State of Baden-Württemberg	2023	General public services	Pilot	Internal management
LLM "Made in Germany"	National	OpenGPT-X	2022	General public services	Planned	Analysis, monitoring and regulatory research

Source: Author's formulation, compiled from JRT publications repository (2025)

Figure 4.5. Gen-AI initiatives' contributions to public service improvements in Germany (2025)



Source: Author's formulation, compiled from JRT publications repository (2025)

While the aforementioned initiatives already contributed to the German public sector, however those tools merely contribute to two primary areas, namely (1) personalised services and (2) new services or channels. Figure 4.7 indicates a critical need for the German public sector to improve the other three key areas, including expanding the exert of AI initiatives to (1) promote more responsive, efficient and cost-effective services; (2) increase the quality of public service innovation and services; and (3) enable citizen-centric services. (Figure 4.5).

4.1.8 Market concentration in Sustainable AI projects

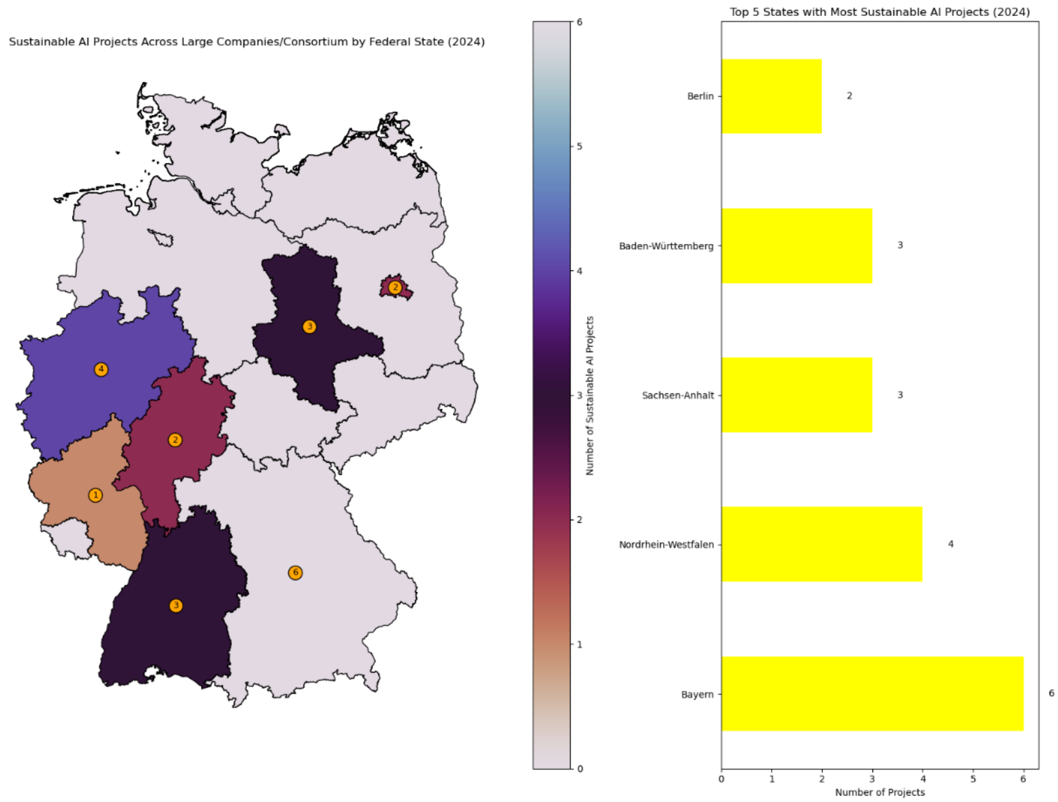
Results from the interview further underscore the imperative of promoting equal AI market contestability in Germany, since there is a tendency of growing narrow market concentration on AI development and deployment only to a few larger corporations and federal states.

> *"So, we always said sustainable AI should not endanger social cohesion. It should stay within the planetary boundaries. And it should not aggravate economic concentration." (Interviewee 1, with a background of Civil Society Orgnisation and Academia).*

> *"So you have states that don't have anything, and then you have states like Bavaria and North Rhine-Westphalia, who are also the most wealthy Bundesländer, who have big initiatives. But I think that it's not only AI that exists in, for example, economic promotion offices abroad. So I was in Japan last November, and there's a Bavarian office in Tokyo that only does like Bavarian economic promotion. And there's an office for North Rhine-Westphalia that only does promotion for the state of North Rhine-Westphalia. But there's no office of Brandenburg or... Yeah."* (Interviewee 2, with a background as an AI expert at International Organisation).

Southern and western Germany dominate the sustainable AI projects across large companies or consortiums, owing to their more established research and development centres and robust industrial ecosystems. Bayern is at the forefront (6 projects), followed by Nordrhein-Westfalen (4 projects) and Baden-Württemberg and Sachsen-Anhalt (3 projects each). Some renowned initiatives comprise Alice III in Bayern, Designetz (integration of renewable energies into the supply system) in Nordrhein-Westfalen, and machine maintenance with noise detection in Baden-Württemberg (Figure 4.6).

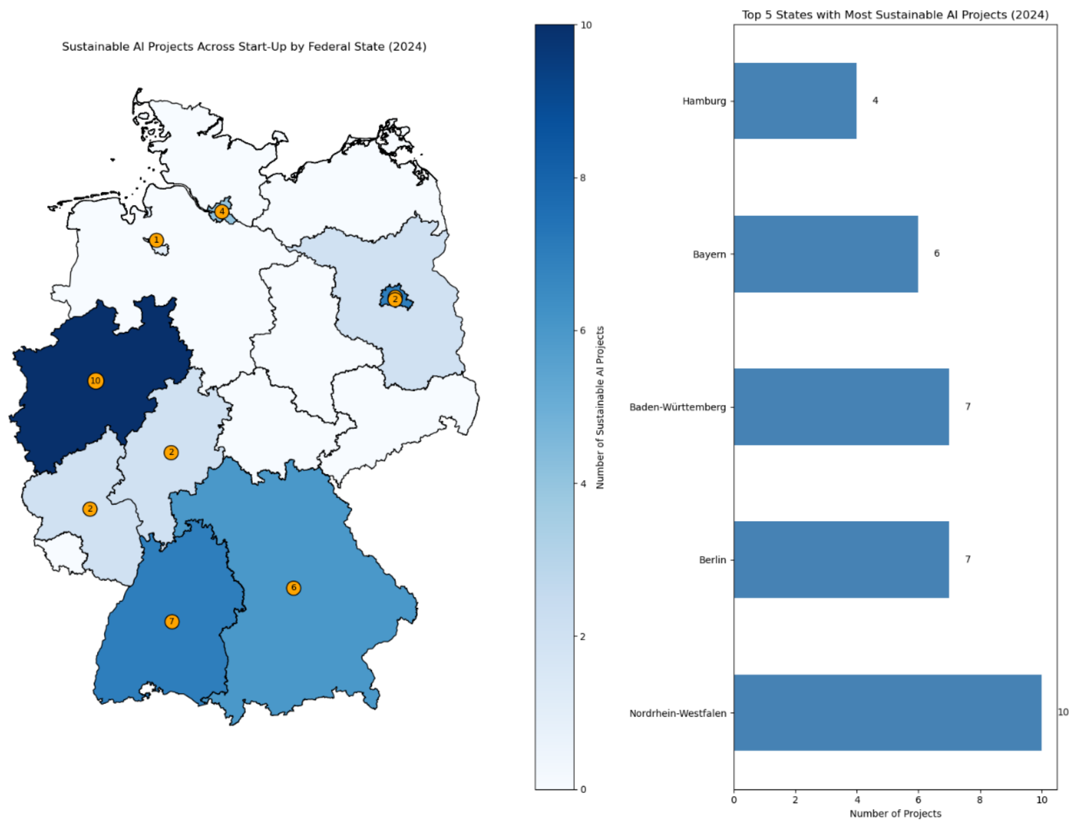
Figure 4.6. Sustainable AI projects across large companies/consortium by Federal State (2024)



Source: Author's formulation, extracted from www.plattform-lernended-systeme.de. The figure uses a gradient map, where darker tones signify higher concentrations. (2025)

Similar to the previous figure, the southern and western parts of Germany remain the central area for spurring start-up-led sustainable AI projects due to their robust start-up ecosystems complemented by advanced research and development centres. Nordrhein-Westfalen tops the rank with 10 projects, followed by Baden-Württemberg (7 projects), Bayern (6 projects) and Hamburg (4 projects). (Figure 4.7). Several highlighted initiatives encompass the app Mona Energy in Nordrhein-Westfalen, KIOWA (predictive maintenance for turning machines) in Baden-Württemberg, and an automatic image recognition software for plant damage in Berlin.

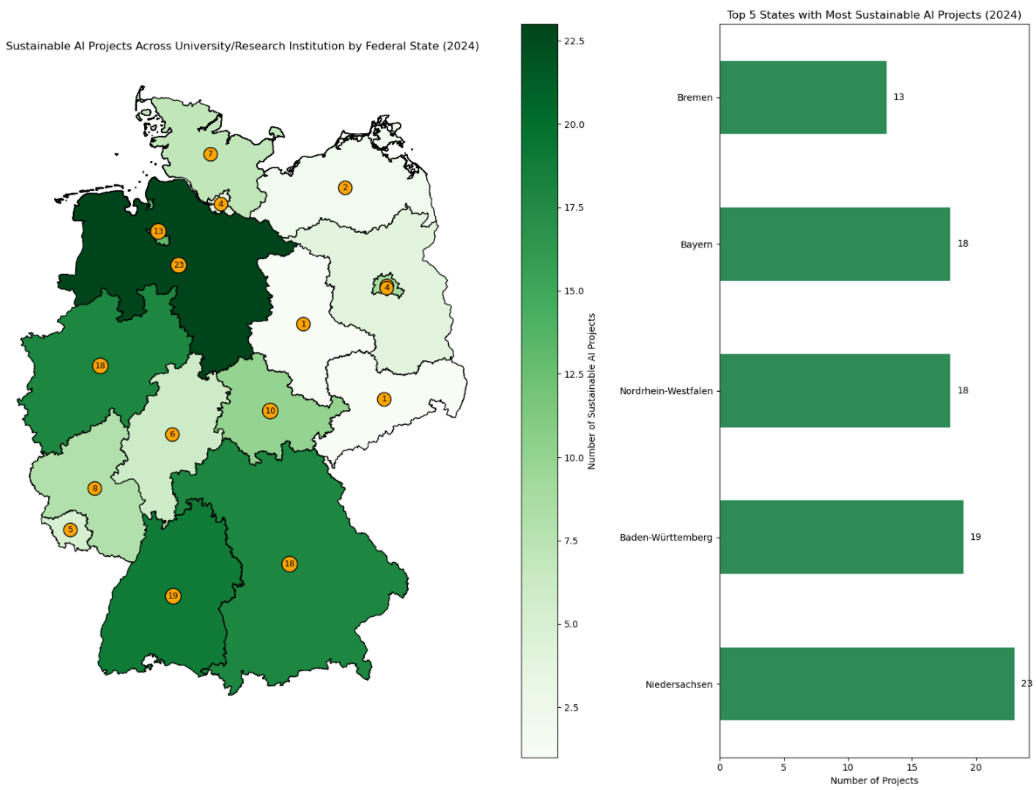
Figure 4.7. Sustainable AI projects across Start-Up by Federal State (2024)



Source: Author's formulation, extracted from www.plattform-lernended-systeme.de. The figure uses a gradient map, where darker tones signify higher concentrations. (2025)

Meanwhile sustainable AI projects across university/research institutions exhibit a more equally distributed trend in Germany (Figure 4.11). Niedersachsen leads at the forefront with 23 projects, followed by Baden-Württemberg (19 projects), Nordrhein-Westfalen and Bayern (18 projects each), and Bremen (13 projects). Notable initiatives include AVKVIN (digitalised methods in waste incineration power plants in Niedersachsen), Desire4Electronics (sustainable remanufacturing with machine learning methods) in Baden-Württemberg, and AirCarbon III (AI in fibre technology) in Bayern. (Figure 4.8).

Figure 4.8. Sustainable AI projects across University/Research institution by Federal State (2024)



Source: Author's formulation, extracted from www.plattform-lernended-systeme.de. The figure uses a gradient map, where darker tones signify higher concentrations. (2025)

4.1.9 Shortage of highly skilled workers

Germany stands at the forefront of countries with a significant increase in the need for IT skills linked to sustainability among the European Union countries. From 2019 to 2024, Germany experiences a considerable rise of up to 265 per cent. In terms of the need in 2024, Germany stands at the top, with the demand of 3,042,967 professionals, significantly surpassing other counterparts such as France (2,073,791), Austria (557,551) and Italy (546,681). (Table 4.4).

Table 4.4. Demand for IT skills related to sustainability (OECD, 2025)

Country	2019	2020	2021	2022	2024
Germany	833309	1303705	1735739	2002348	3042967
France	590120	949004	1227804	1460356	2073791
Austria	111135	183354	265428	366048	557551

Country	2019	2020	2021	2022	2024
Italy	87249	117045	261989	354079	546817

Source: Author’s formulation, compiled from OECD.AI (2025)

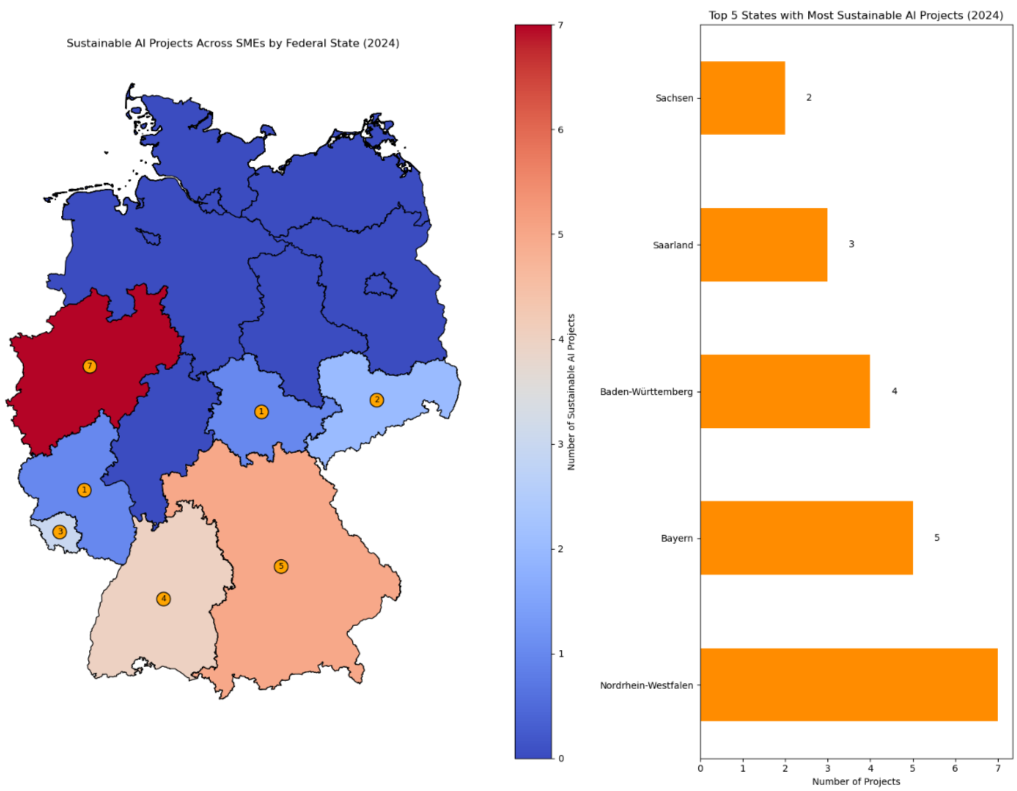
However, pursuant to Interviewee 4, there remains an inadequate supply of highly skilled professionals in the data centre industry, the sector that critically contributes to the sustainability of AI systems, compared to its rising demand. The need for skilled workers in this area is even regarded as more important than fast permit and regulatory requirements.

> *“[…] skilled professionals was one of the things that was rated, actually, was rated as the fifth most important factor for the German market, so even more important than fast permits and regulatory requirements. So, it's a very, very important topic. So, not as bad as the electricity prices or as the slow permitting processes, but it is rated as a big problem already now. I mean, in most sectors, we have this problem, not only in the data centre industry, but obviously the data centre industry is also having big problems to find skilled professionals.”* (Interviewee 4, with a background as an data centre policy expert at a national digital association).

4.1.8 Limited transferability across SMEs

Notwithstanding various AI initiatives in the country (Figure 4.9), the integration of AI within Germany's small and medium-sized organisations (SMEs) remains lesser compared to that of larger corporations, primarily owing to structural and knowledge-related constraints. Although national and regional initiatives seek to democratise access to AI technologies, small and medium-sized enterprises are often hampered by deficiencies in expertise, workforce, and understanding of practical applications.

Figure 4.9. Sustainable AI projects across SMEs by Federal State (2024)



Source: Author’s formulation (2025), extracted from www.plattform-lernended-systeme.de. The figure uses a gradient map, where darker tones signify higher concentrations.

Interviewee 2 highlighted the abundance of governmental initiatives designed to facilitate AI integration within the SME sector. Projects like the Green AI Hub Mittelstand were referenced as proactive initiatives to integrate AI talent directly into enterprises. These initiatives are enhanced by Germany's robust institutional research framework, such as the Fraunhofer Society, which acts as a conduit between theoretical research and industrial implementation. Nevertheless, despite these structural supports, numerous SMEs find it arduous to convert this potential into tangible AI applications:

> *“And I think that that's actually where they do a good job already. Like there's the, for example, I don't know if you've seen it, the Green AI Hub in Mittelstand. That's exactly what they're trying to, like, I think you get a free kind of AI scientist to come to your SME for like a couple of months. But it's hard. But not because of lack of trying. Like they are*

> *really, there are a lot of initiatives for SMEs. They're really trying to bring it to the market there. And then you also have this entire system of Germany, of Fraunhofer, which bridge theory and practitioners also in the Mittelstand. So I think, yeah, I think they're trying a lot. But the problem is, again, more structural, not only in AI."* (Interviewee 2, with a background as an AI expert at an International Organisation)

Furthermore, Interviewee 2 outlined that the deficiency in technical capacity and AI literacy among SMEs starkly contrasts with larger firms like Siemens, who advantageously possess robust research and development divisions and strong affiliations with academic institutions. In these firms, the existence of specialised AI departments and access to university-educated professionals guarantees a systemised, seamless transition from theory to application.

> *"So, to be fair, there are a lot of initiatives already for SMEs, kind of AI for SMEs, not only for sustainability, but broader. But they're facing the known problems of SMEs. They either don't know really what AI is, how to use it, how to apply it, what kind of problems you can solve with it. They don't have the people. Like Siemens here in Munich, they have an AI department with like hundreds of AI scientists. And they have a corporation with the University of Munich where they get all the talent. So like for them, it's easy. But for SMEs, it's really a lack of know-how, a lack of understanding which problems can be solved with AI."* (Interviewee 2, with a background as an AI expert at an International Organisation)

4.2 The Potential Trilemma of Sustainable AI in Germany

The interview results reveal the potential inherent trade-offs between the three pillars of sustainability, namely social, economic, and ecological, emphasising that balancing them would be arduous and even yield conflicts. This further reflects the multifaceted challenge in applying sustainability frameworks to research and ethical practices to promote more sustainable AI practices. Interviewee 1 underscored the inherent disputes within the concept of sustainability, notably in the AI system practice, emphasising that aiming to achieve certain sustainability pillars may potentially compromise others.

> *"You can have a conflict of an indicator in the social dimension, for instance. You would want to have a data minimalistic approach to AI, which could endanger the aim of having a non-discriminatory AI. So, there are many, many conflicts between different criteria and*

> *indicators. There are also a lot of synergies, of course. And so, we didn't consider the set of indicators and criteria to be just some sort of orientation. Because what means sustainable AI has to be decided for every development process, for every system individually. And within every system, you would have to negotiate these kinds of conflicts. And this is not new for sustainability approaches, right? You have conflicts and trade-offs all the time."* (Interviewee 1, with a background in Civil Society Organisation and Academia).

Interviewee 3 corroborated the previous argument by examining the potential conflicts that exist across all pillars of sustainability, which in this context refers to economic, ecological, and social sustainability. Interviewee 3 underlined that such trade-offs would occur innately and there is no need to prioritise one over three other dimensions in undertaking sustainable AI practices.

> *"I don't think that there is one pillar which is more critical than another pillar because in every pillar there are challenges which are important."* (Interviewee 3, with a background of Civil Society Organisation and Academia).

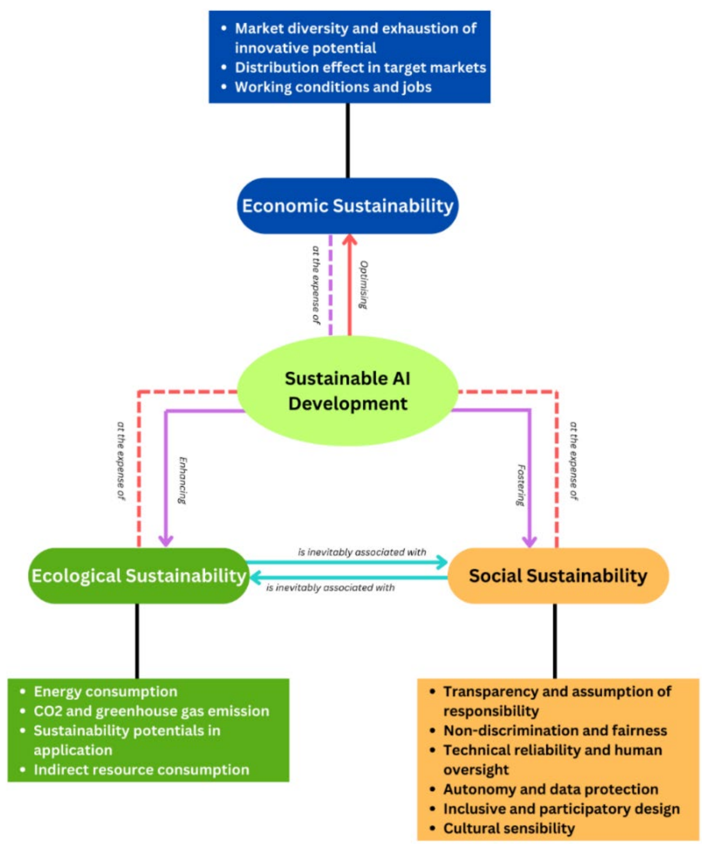
However, there remains an imbalance within the public discourse in Germany, which is leaning to debate about the ecological sustainability more compared to the other two critical dimensions, social and economic sustainability. Not to mention, limited public understanding about the sustainability pillars, for instance, environmental impacts from harnessing digital and technological infrastructure, also exacerbates the efforts of promoting sustainable AI in the practice.

> *"And I think it's also... I think at the moment we are much more debating about the environmental impacts because that is the thing which people don't always know. So they don't know that there's a huge energy demand and huge water consumption and all this stuff behind all the digital infrastructure we need for AI. So, I think this course is a little bit more arising, I would say."* (Interviewee 3, with a background of Civil Society Organisation and Academia).

5. DISCUSSION

This section addresses the two proposed research questions: (1) "What challenges does Germany encounter in promoting sustainable AI?" and (2) "How can Germany navigate the trilemma of fostering sustainable AI?" The presentation outlines five main challenges Germany faces in promoting sustainable AI practices, including issues that could hinder the country's efforts based on the 13 sustainability criteria of AI (Rohde et al., 2024). Subsequently, the second sub-section examines the research question of "How can Germany navigate the trilemma of promoting sustainable AI?" built on the existing challenges presented in the first sub-section and on the conceptualised theoretical framework presented in Section 3 (Figure 5.1) to analyse how the country should navigate potential trade-offs yielded from simultaneously advancing the three pillars of sustainability: (1) ecology; (2) social; and (3) economic.

Figure 5.1. Conceptualised Theoretical Framework



Source: Author's formulation (2025) based on the Three Pillar Model of Sustainable Development (Barbier, 1987), the Sustainability Criteria for AI (Rohde et al., 2024), and the contemporary Theory of Sustainable Development (Lee & Park, 2021)

5.1 Challenges encountered by Germany in fostering Sustainable AI practices

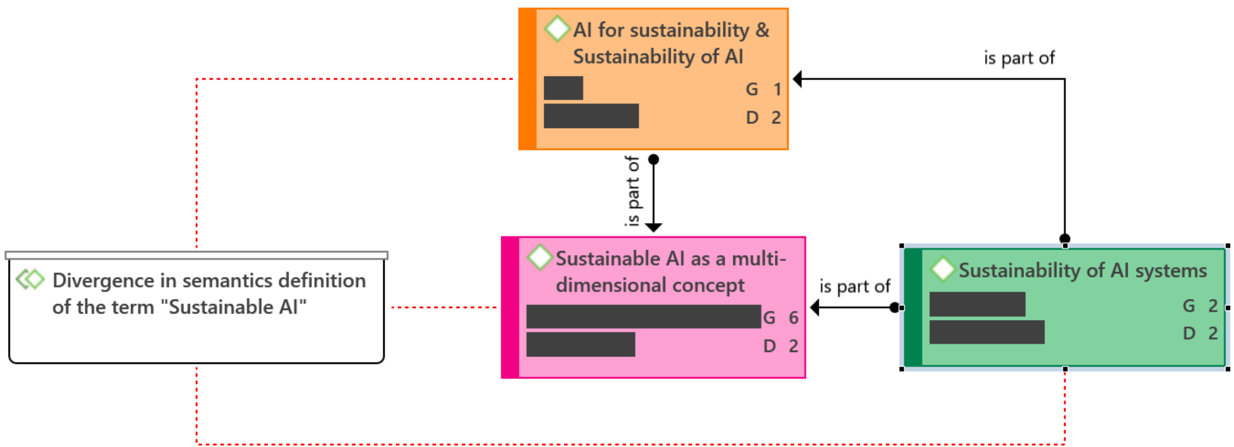
The Sustainability Criteria for AI (Rohde et al., 2024) encompass three fundamental sustainability facets, including (1) social sustainability; (2) economic sustainability; and (3) ecological sustainability. According to the criteria, social sustainability includes 16 points, while economic sustainability and ecological sustainability comprise 3 and 4 points, respectively. Predicated on the findings, Germany has undertaken significant efforts to promote the three sustainability criteria for AI, albeit the practical actions and ethical debates are predominated by ecological sustainability and leave room for improvement for economic and social sustainability. In addition, the findings also signify two other bottlenecks that may potentially impede the advancement of sustainable AI in Germany, including the need to converge the definition of the term "sustainable AI" and improve the betterment of AI governance in the country, as further presented below.

5.1.1 Common grounds on defining the term "Sustainable AI"

Germany stands at the forefront of academic and ethical debates on the term "sustainable AI", yet in practice there remain fragmented perceptions to define this emerging terminology. Findings from the literature review signify three primary definitions of the term "sustainable AI", comprising (1) AI as an eco-friendliness AI system (Vartziotis); (2) AI as a green technology (Verdecchia, 2022; Tabbakh, 2023; Castelanos, 2023); and (3) AI as a sustainable system (Mercier, 2022; Trinh, 2024; Wang, 2024).

Meanwhile, the semi-structured interview results showcase a slight difference in terms of perceiving the term (Figure 5.2).The notable commonality lies in the similar perceptions of the term "sustainable AI" as a sustainable AI system, while the current common understanding of the term refers to the definition coined by AI ethicist Van Wynsberghe (2021), referring to a movement to foster change in the entire lifecycle of AI products (e.g., idea generation, training, re-tuning, implementation, governance) towards greater ecological integrity and social justice.

Figure 5.2. Divergence in semantics of the term "Sustainable AI"



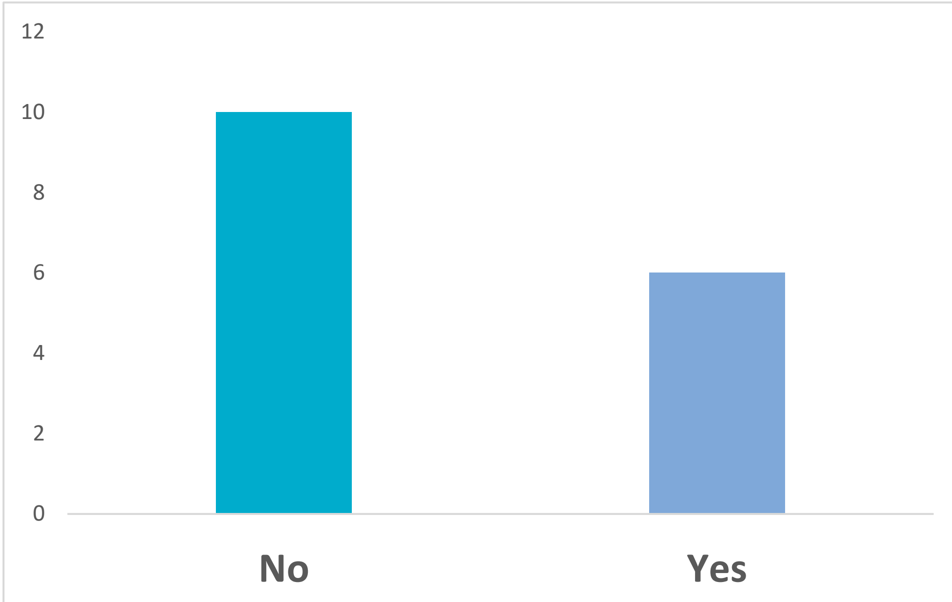
Source: Author's formulation based on interview findings (2025)

In contrast, some also argue that sustainable AI narrowly refers to initiatives linked to tackling environmental issues, which are predominantly based on techno-optimism beliefs and alluring political promises. There is an imperative to find common ground by converging differences in understanding the term "sustainable AI" in Germany; thus, future policy initiatives and research can drive impacts on a more overarching scope rather than merely addressing ecological-related issues.

5.1.2 AI governance

Germany has performed a solid nationwide AI initiative, including publishing a dedicated AI national strategy (*der Nationalen KI-Strategie der Bundesregierung*), yet critical structural challenges surrounding AI governance remain menacing for the country and may impede Germany in vying with other global AI key players, such as the United States and China (Figure 5.x). Although there is already a national AI initiative in place, AI governance practices are still fragmented both vertically and horizontally across the federal ministries and federal states. One piece of stark evidence is the absence of a central national office or national body assigned to conduct oversight and to harmonise the implementation of the national AI strategy. This is even exacerbated by the lack of coordination and silos in implementing AI initiatives among the government actors, resulting in various duplications of similar projects or initiatives. Not to mention, it appears that not all federal states have a granular AI strategy in place (Table 5.3) that signifies disparity in terms of governing AI in the policy levers.

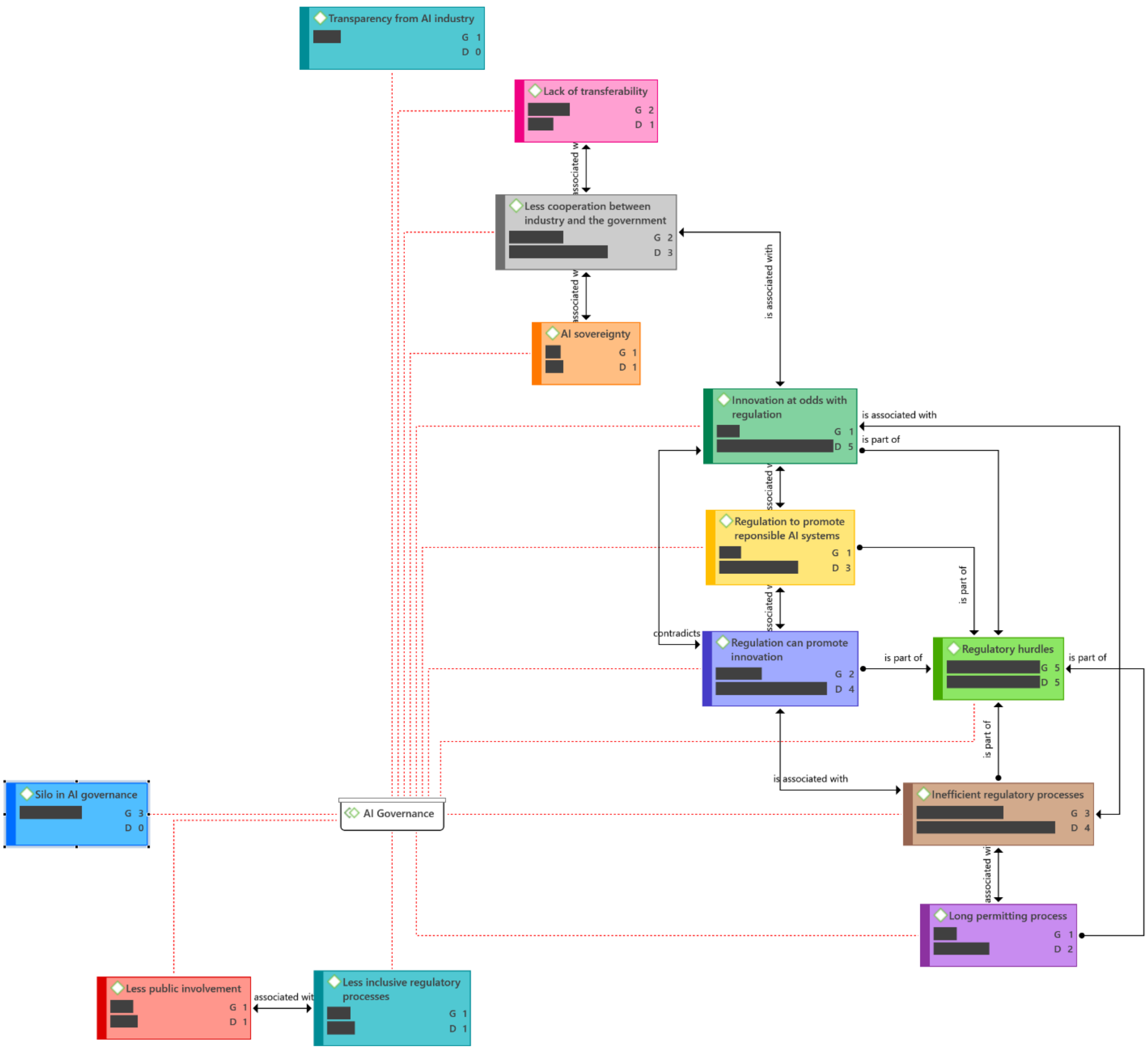
Figure 5.3. Availability of any dedicated AI Framework in German Federal States



Source: Author's formulation extracted from www.ki-strategie-deutschland.de (2025)

Another notable entrenched challenge lies in the regulatory practices that is more focused on regulating energy measurements, including to data centres, instead of promoting an overarching sustainable AI practice, such as addressing potential harmful consequences from harnessing AI socially, economically, and ecologically, as well as producing a sustainable AI system. For instance, the establishment of the Energy Efficiency Act (EnEfG) and overstrict application of the EU Energy Efficiency Directive often backfire on the small and medium enterprises (SMEs) that is not viable and feasible to comply with the law. Moreover, finding from interviews also show that bureaucratic issues, such as long permitting processes on building new AI infrastructures affect the scaling process of AI advancement in the country.

Figure 5.4. Challenges in AI governance



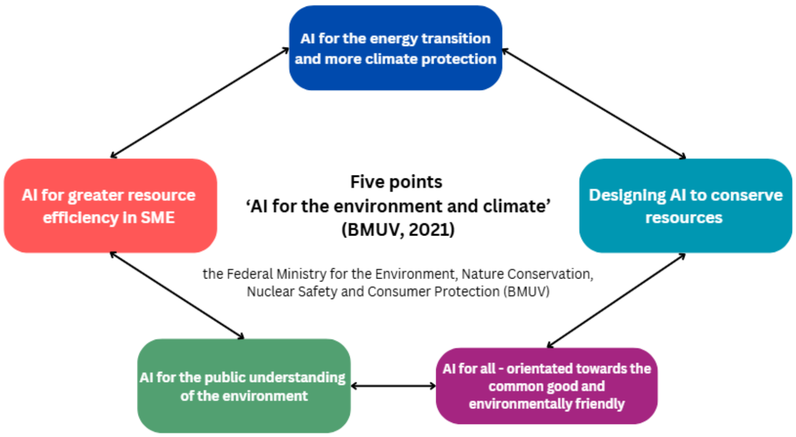
Source: Author's formulation based on interview findings (2025)

5.1.3 Ecological sustainability

Germany leadership in promoting ecological sustainability through AI is evident in the Federal Government's robust robust commitment to utilising AI for environmental conservation and climate protection, as outlined in the five principles of "AI for the Environment and Climate" (Figure 5.5), encompassing (1) AI for the energy transition and more climate protection (*KI für die Energiewende und mehr Klimaschutz*); (2) Designing AI to conserve resources (*KI ressourcenschonend gestalten*); (3) AI for greater resource efficiency in SME (*KI für mehr*

Resoourceneffizienz im Mittelstand); (4) AI for all – orientated towards the common good and environmentally friendly (*KI für alle – gemeinwohlorientiert und umweltgerecht*); (5) AI for the public understanding of the environment (*KI für das öffentliche Umweltverständnis*).

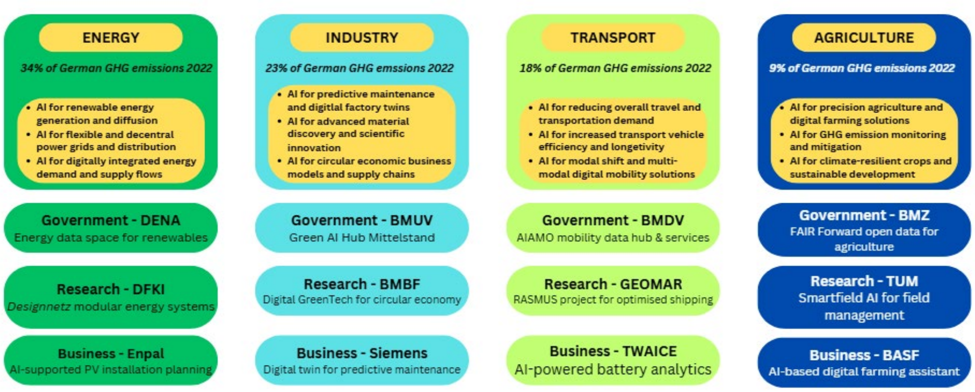
Figure 5.5. Five Principles of "AI for the Environment and Climate" (*KI für Umwelt und Klima*)



Source: Author's formulation redrawn from Funf-Punkte-Programm „Künstliche Intelligenz für Umwelt und Klima" (BMUV, 2021)

Furthermore, Germany currently leads EU member states in in effectively leveraging the benefits of AI and environmental sustainability efforts, undergirded by cross-sector collaborations involving federal ministries, academia, industry, civil society, and states (OECD, 2024). These initiatives encompass the energy, industry, transport, and agriculture sectors, which are considered as Germany's most contributing greenhouse gas emissions with percentages of 34 per cent, 23 per cent, 18 per cent, and 9 per cent, respectively (Figure 5.6).

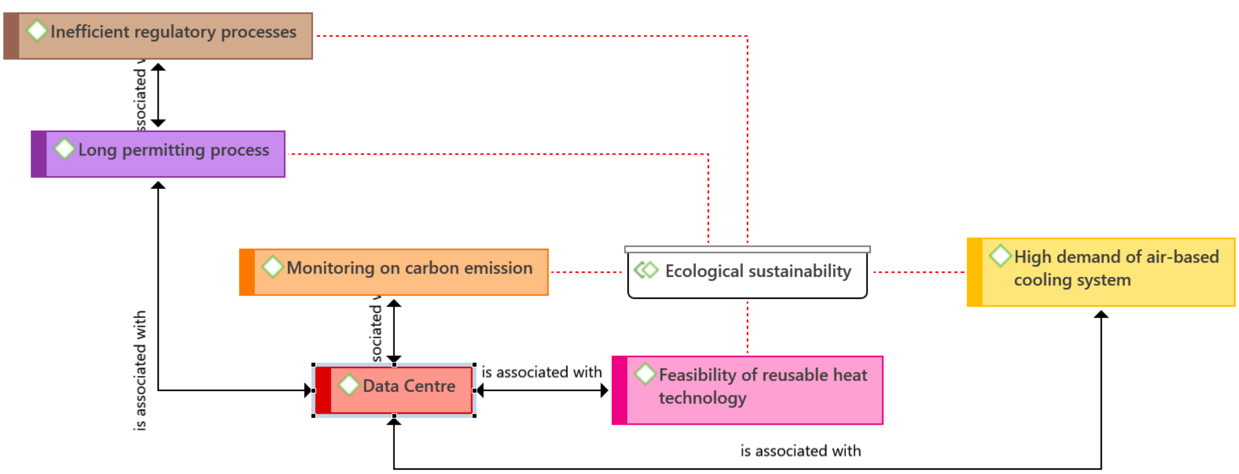
Figure 5.6. Several Initiatives in the German AI Ecosystem for Rapid Decarbonisation Across



Source: Author's formulation based on OECD's AI Review of Germany (2024)

However, several factors remain menacing and potentially impede Germany to leverage AI for yielding sustainable ecological innovations. *First*, regulatory inefficiencies that often hamper the industry to promote sustainable innovation and practices, for instance, the overstrict regulatory enforcement on the mandatory of energy reuse factors and the utilisation of power usage effectiveness caps that evidently unfeasible for most industries, especially the co-location data centres with minimal control capacity. *Second*, the sustainable practices to promote sustainable AI often lack of economic feasibility and is exacerbated by the incapacity of industries in Germany to reutilise waste heat and exert air-based cooling systems to promote sustainable practices throughout the AI cycle. (Figure 5.7).

Figure 5.7. Challenges in ecological sustainability

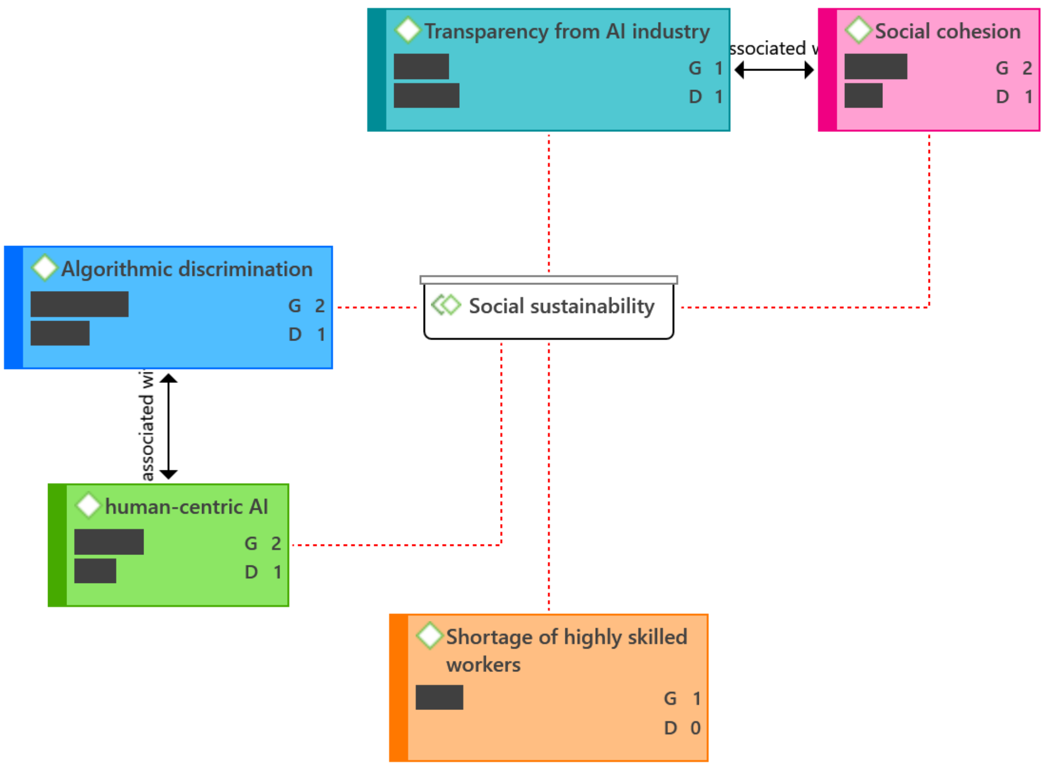


Source: Author's formulation based on interview findings (2025)

5.1.4 Social sustainability

The concept of social sustainability often arises in ethical debates in Germany as part of a multidimensional framework; however, it is less frequently discussed compared to ecological sustainability. Promoting social sustainability becomes imperative in driving societal impacts from harnessing AI, including distributing social equity and fairness (Oyadeyo, 2025), enhancing social cohesion (Rohde, 2024), spurring responsible AI-led innovation (Habibipour, 2024), and upholding human-centred values in the AI lifecycle (Khosravi, 2024). (Figure 5.8). Often overlooked, in addition to widely acknowledged socio-ethical issues such as algorithmic transparency and human-centric AI development, is the shortage of highly skilled labour. According to the latest data from OECD (2025), Germany possesses a considerable demand for IT skills related to sustainability, with up to 3,042,967 labours, significantly higher compared to other EU counterparts such as France (2,073,791), Austria (557,551) and Italy (546,817), making it critical to meet the demands; otherwise, it may hamper the country's aspiration to promote sustainable AI practices in the future.

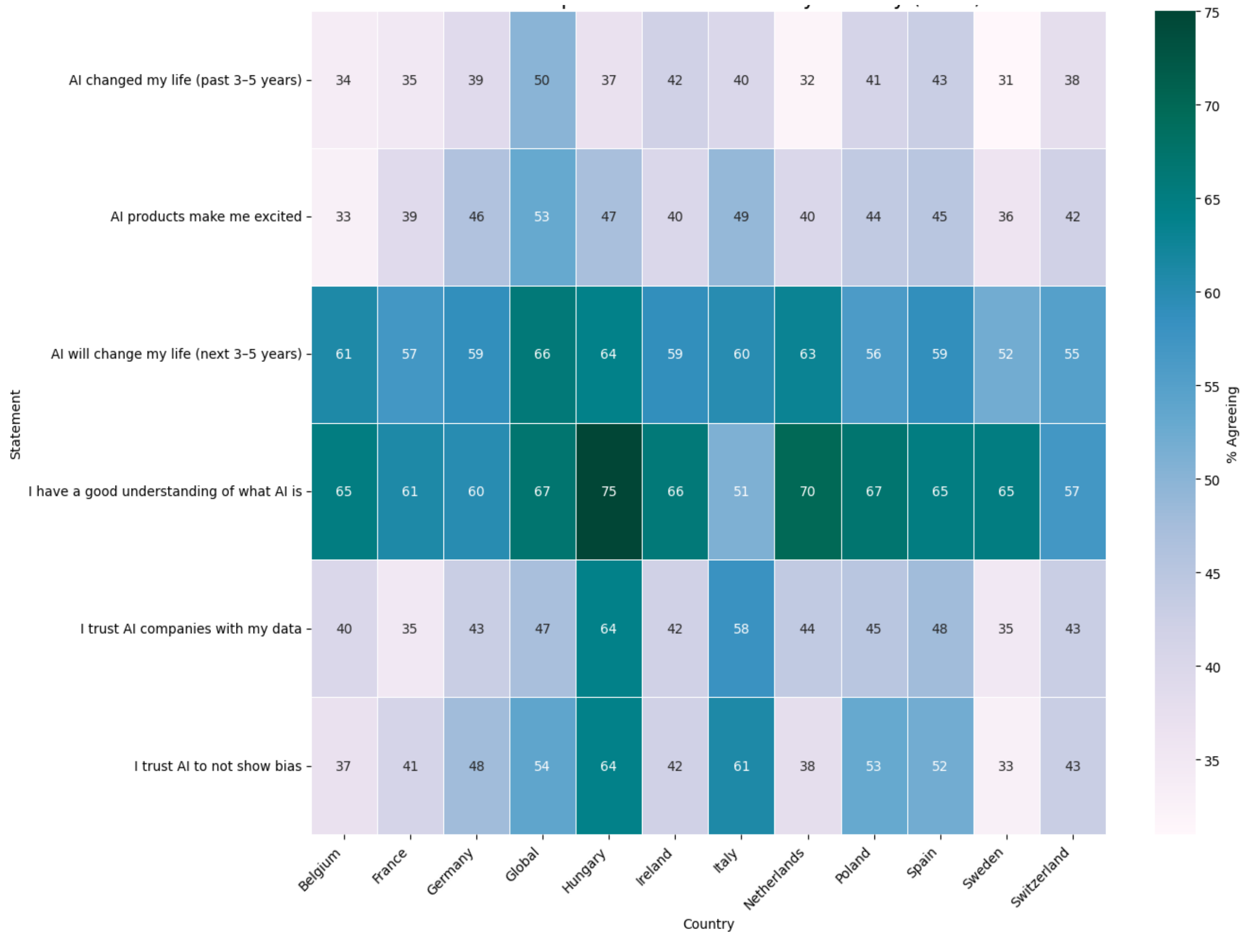
Figure 5.8. Challenges in social sustainability



Source: Author's formulation based on interview findings (2025)

The recent data extracted from the Stanford AI Index (2025) justifies the emerging social concerns growing among Germans, showcasing a lack of optimism and excitement about utilising AI products and services. (Figure 5.9). Notable concern lies in the trust of users in AI companies in dealing with the users' private data, scoring solely 43 per cent, lower than the global average of 47 per cent, making it critical for the policymakers in Germany to take into account the importance of safeguarding users' data used by companies, including for undertaking an intensive large data training in the future.

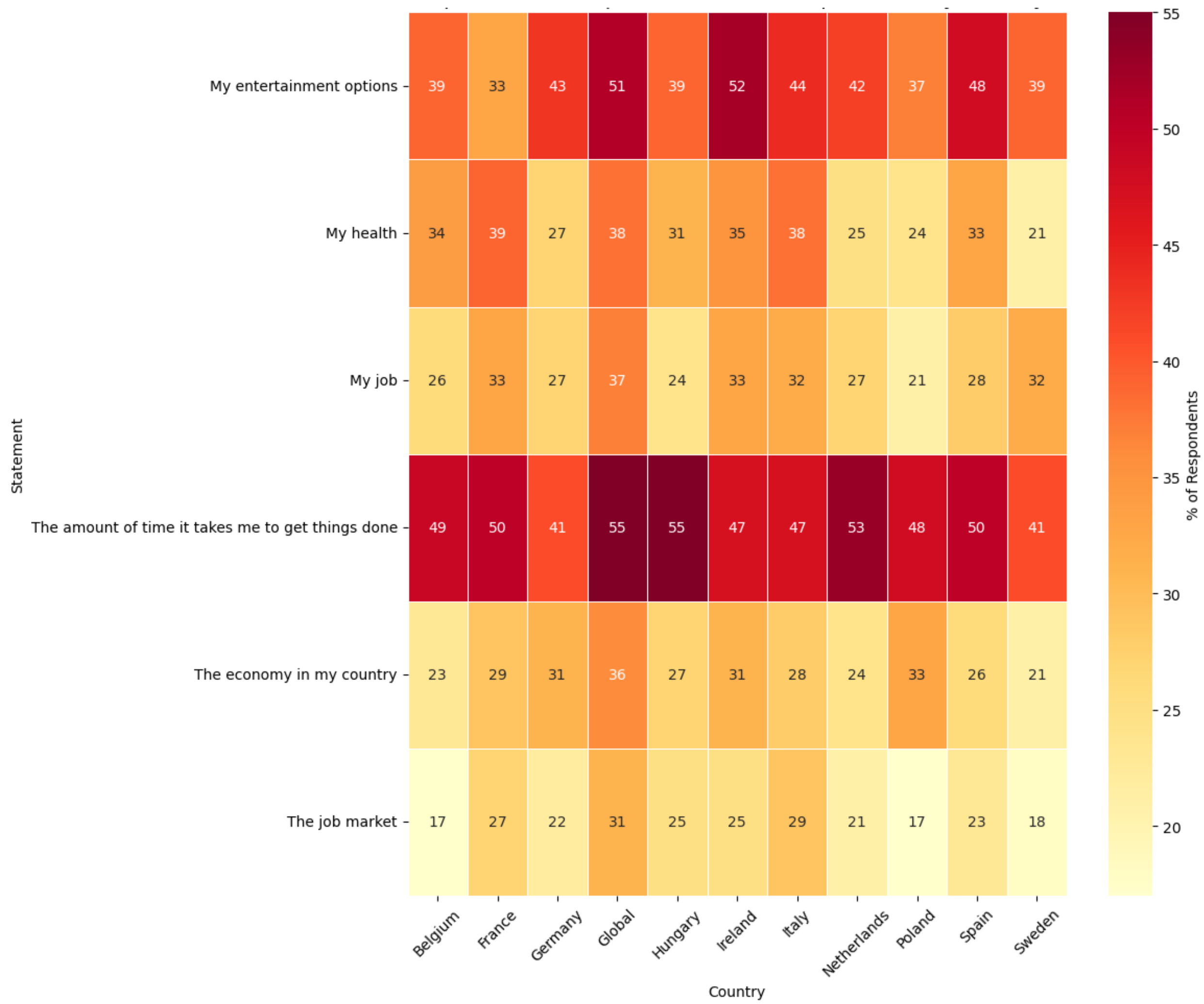
Figure 5.9. Public trust on AI products and services by country (2025)



Source: Author's formulation (2025), extracted from the open-sourced dataset of the Standford AI Index 2025

According to the same index's dataset, Germany (41 per cent) ranks lower compared to the global average (55 per cent) and Hungary (55 per cent) in perceiving AI as a tool to expedite task completion. In terms of well-being, solely 27 per cent of German respondents see AI providing a positive outcome for their health, scoring below the global average of 38 per cent and trailing behind countries like France (39 per cent) and Italy (35 per cent), while exceeding Sweden (21 per cent). Another measured indicator is employment-related opinions, with only 27 per cent of Germans expecting that AI would improve the quality of their work and 22 per cent believing in a positive effect on the labour market. This reflects the low level of optimism about the potential positive impact of AI on socio-economic matters and growing concerns about AI that may affect jobs, health, and productivity. (Figure 5.10).

Figure 5.10. Public opinions on the potential of AI to improve life by country (2025)

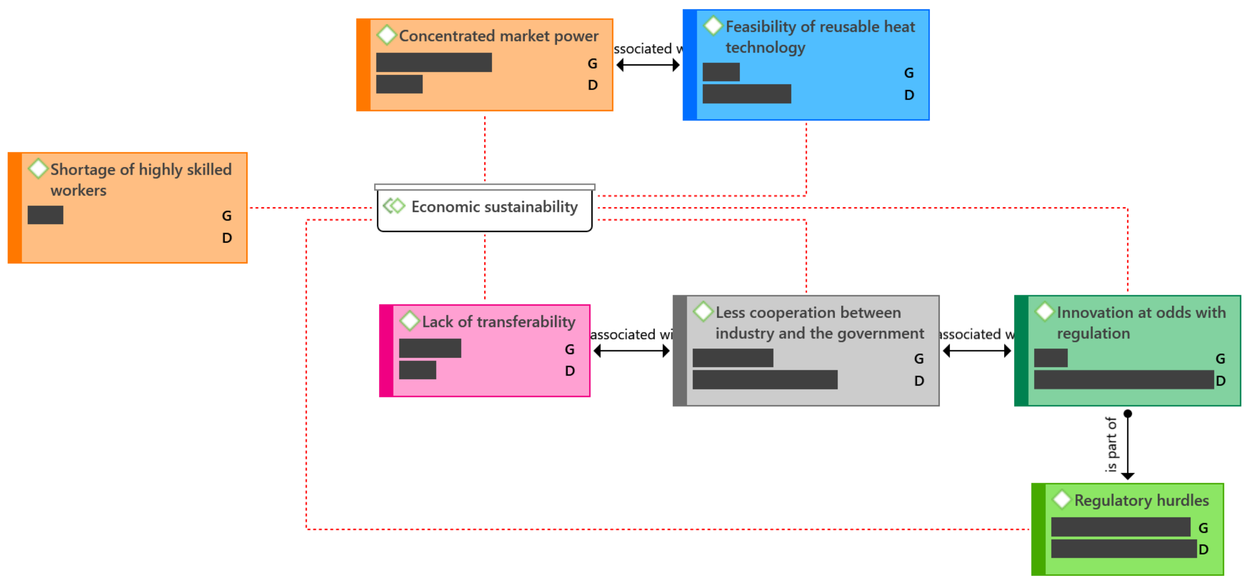


Source: Author's formulation (2025), extracted from the open-sourced dataset of the Standford AI Index 2025

5.1.5 Economic sustainability

As AI is perceived as an impetus for economic growth by enhancing productivity, thus advancing AI-led innovations for the economy while safeguarding planetary boundaries simultaneously becomes imperative (Balcioglu, 2024; Roberts, 2024; Rohde, 2024). In essence, economic sustainability aims to harness AI to boost economic gains while bolstering sustainable practices at the same time (Siddik, 2025; Roberts, 2024). Amidst its relatively advanced AI ecosystem, economic sustainability remains less discussed in the realm of sustainable AI, as the focus merely sheds light on ecological sustainability. (Figure 5.11).

Figure 5.11. Challenges in economic sustainability



Source: Author's formulation based on interview findings (2025)

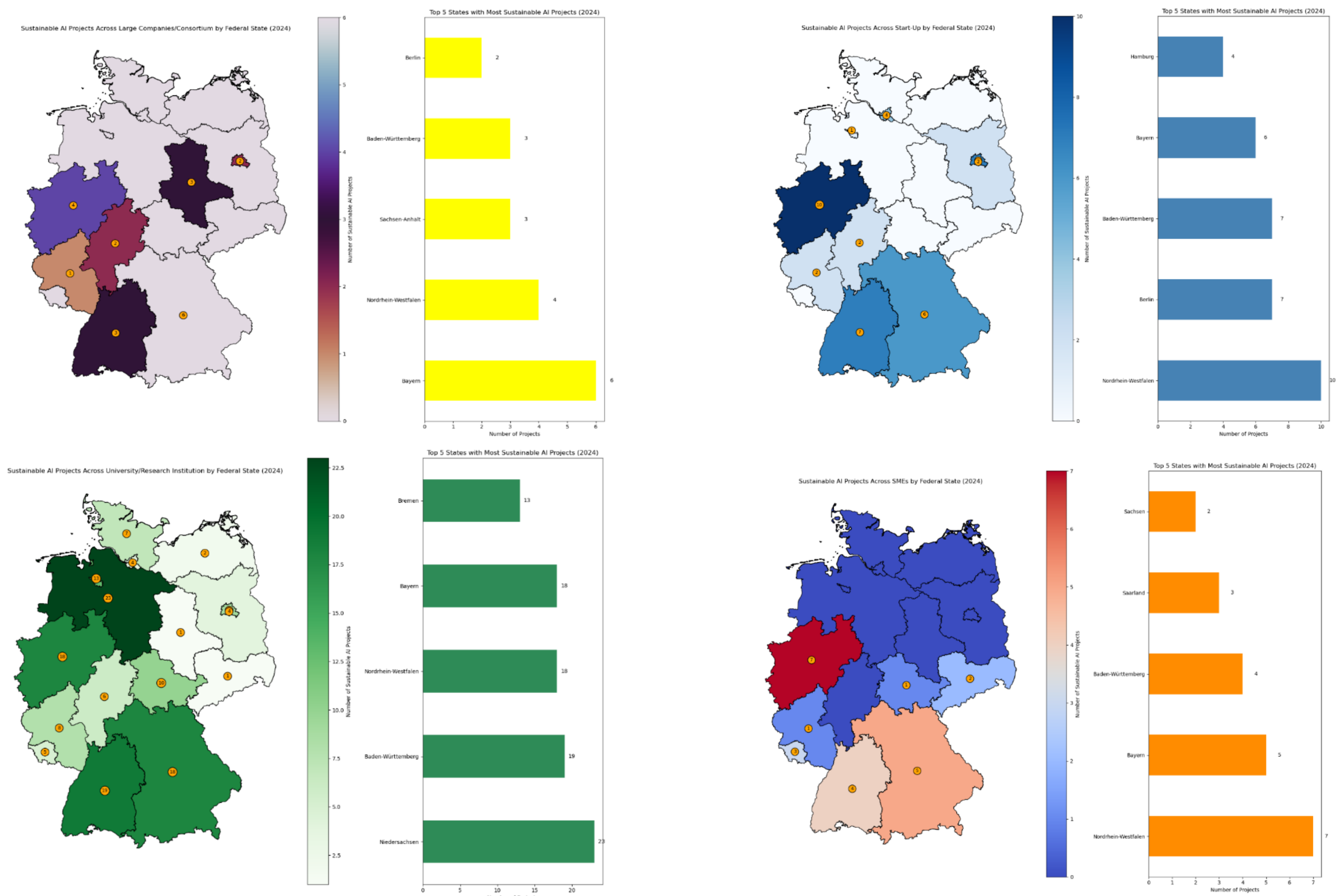
Acknowledging economic sustainability is critical since the huge investment poured into the AIe AI industry should be worth return on investment (ROI) and be equitably distributed to the society for improving the well-being of the people. Nonetheless, four primary hurdles are encountered by both private and public sectors in the country.

First, there remains a lingering concentration on the AIe AI market in Germany, where AI infrastructures and resources are controlled by domestic and international big technology companies (big tech). This is aggravated by the fact that the development and deployment of AI is centralised in several affluent states like Nordrhein-Westfalen and Bavaria, while other smaller Bundesländer are lagging behind. The phenomenon is understandable due to the uneven distribution of prerequisite AI resources and infrastructures among the *Bundesländer*, resulting in a gap in the level of competitiveness and development of sustainable AI practices. (Figure 5.12).

Second, the attainment of economic gains hinges on the effective transferability of AI deployment into beneficial practices for society. This is the area where Germany needs to improve, although there are already numerous good practices on transferability, and the federal government already embedded this issue in the BMBF-*Aktionsplan Kunstliche Intelligenz*. There is an urgent need to amplify the current established transferability ecosystem by enhancing cooperation between start-ups, research universities/institutions, SMEs, CSOs, and other relevant stakeholders to boost AI competitiveness and narrow the gap of AI development among the *Bundesländer.*

Third, a stringent regulatory framework in Germany is evidently impeding the massive potential of AI benefits to the country, in contrast to other EU counterparts who enforce more lenient legislation, like France and the Nordic countries. These regulatory hurdles, aggravated by bureaucratic complexities, tend to block innovation and the provision of key AI infrastructures. Fourth, since Germany mostly relies on external tech infrastructures as its AI foundations, for instance, the Amazon cloud services, this raises the imperative of shifting towards sovereignty to evade the future harmful consequences, including to national security.

Figure 5.12. Distribution of Sustainable AI projects in Germany by Federal State (2024)



Source: Author’s formulation (2025), extracted from www.plattform-lernended-systeme.de. The figure uses a gradient map, where darker tones indicate higher concentrations.

5.2 Navigating the trilemma of Sustainable AI

Academic articles remain meagre in discussing the trilemma of sustainable AI, which in general may refer to the trade-offs between three primary aspects of AI systems, namely (1) social; (2) economic; and (3) environmental facets. In the contemporary theory of sustainable development, optimising the three objectives will be at odds with each other, making it solely feasible to opt for two out of three facets at the same time. For instance, spurring economic growth frequently yields harmful consequences for social equity and environmental preservation. Conversely, prioritising social equity, including social fairness, justice, and environmental protection, may impede economic growth (Lee & Park, 2021).

In the current state of AI development in Germany, it can be argued that the country is focusing heavily on ecological sustainability, moderately on social sustainability, and underdeveloped economic sustainability (Table 5.1). This reflects the previously presented conceptualised framework built on the Three Pillar Model of Sustainable Development (Barbier, 1987), the Sustainability Criteria for AI (Rohde et al., 2024), and the contemporary Theory of Sustainable Development (Lee & Park, 2021), justifying that it remains unfeasible to maximise the three pillars of sustainability at the same time. Instead, merely two out of three pillars can be optimised simultaneously, which in this context means Germany could only well develop ecological and social sustainability.

Table 5.1 The current state of priorities among the three pillars of sustainability

Pillar of sustainability	Current state of priority	Potential trade-offs
Ecological sustainability	High	Complex regulatory compliance and economic hurdles on SMEs
Social sustainability	Moderate	Low public trust on ethical issues and low optimism on AI's impacts
Economic sustainability	Low	Inequality in AI development among Bundesländer, low ROI for Bundesländer and the country, impediments on AI-led innovations.

Source: Author's formulation (2025)

On one hand, the current state affirms Germany's position as the custodian of environmental and social ethics in the field of AI; however, the evidence indicates that it costs the low performance of economic sustainability. It bears remembering that there is one pillar that is way more critical to the other two, and the opted focus of sustainable AI development is about high-level political decisions after all. The future of AI policies and strategies in Germany should uphold the outstanding ecological and social sustainability practices while also improving the betterment in AI governance and regulatory frameworks to spur economic sustainability practices with its own approaches, or the "German way", rather than mimicking others' practices, including the US'. By undertaking this, Germany would not only be able to navigate the trilemma of sustainable AI but also further bring its unique way to develop and deploy AI, which centres on the robust foundations of ecological and social sustainability that are complemented with positive economic gains that are equitably distributed to society.

6. CONCLUSION

Germany stands at a pivotal moment in its pursuit of advancing sustainable AI practices. Evidence indicates that Germany excels in implementing ecological sustainability and upholding robust socio-ethical values, but it lags in generating economic gains from harnessing AI for society. The bottlenecks lie in structural impediments, including a stringent regulatory framework, silos in AI governance across governmental branches and federal states, and disparity in critical AI resources and infrastructures among the federal states, indicating caveats for Germany to vie with other global key AI players. This situation supports the idea that it's not possible to improve all three areas of sustainability at the same time, and that it's only practical to focus on two out of the three. In this context, Germany is prioritising socio-ecological sustainability facets over economic sustainability that inflicts detrimental effects on the level of scalability, competitiveness, and the distributed economic gains to the society.

On the carrot side, Germany starkly affirms its position as a socio-ecological steward as reflected in its AI strategies and initiatives, making it possible to continue developing and deploying sustainable AI through its “German way”. Instead of compromising such pillars to boost economic aspects of AI, Germany can leverage its strength in establishing rigid legislation and robust ethical aspects with the incorporation of economic viability. Therefore, the future of AI advancement in Germany will not merely become ecologically sustainable but also further socially responsible and economically viable.

This thesis contributes to enriching the literature on sustainable artificial intelligence with a focus on empirical evidence and a specific locus in Germany. Further, this research can provide best practices for other countries in their policymaking efforts to promote sustainable AI, with the ultimate goal of not compromising one sustainability pillar over the others, yet focusing on which pillars are the strongest to provide an opportunity to corroborate and improve the least developed one. With this approach, a country can navigate the trilemma by paving its own way of promoting and governing sustainable AI.

Nevertheless, this study has several limitations. *First*, the absence of granular measurements on each sustainability facet, thus the analysis results may lack nuanced rationale. Further research can address this by creating a sustainability model that provides quantitative equations to explain the phenomenon of the trilemma in fostering sustainable AI initiatives. *Second*, the lack of interviewees for the semi-structured interviews, notably from the German public sector, and limited complementary quantitative datasets available on the internet. To address this, future research may collaborate with wider networks, including start-ups, university partners, CSOs, and the government, to obtain comprehensive data.

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