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University of Oxford

Green Machine Dreams?
A Quantitative Analysis of Sustainable AI Innovation

Candidate number: 1084599
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Thesis submitted in partial fulfilment of the requirement for the degree of MSc in Social Data Science at the Oxford Internet Institute at the University of Oxford

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Abstract

It is indisputable that combating the climate crisis must be a top priority. A promising approach endorsed by many experts is to use artificial intelligence (AI) to mitigate and adapt to the effects of climate change. However, these systems themselves cause significant environmental degradation. Therefore, establishing AI that best contributes to climate action, requires us to both harness the potential of AI to tackle climate impacts and make AI itself more sustainable. Given the urgency of the situation, researchers and developers need to focus their efforts optimally across these objectives. This requires large-scale evidence on the trajectory of sustainable AI innovation, which illuminates areas of progress and neglect. To this aim, the present thesis investigates whether patents, analysed with natural language processing (NLP) techniques, provide a relevant perspective to enrich our understanding of innovation in sustainable AI. Using a text-based classifier, I reveal that the sustainability of AI is severely under-researched, especially environmental impacts that go beyond energy consumption. Inventions which utilise AI to further the sustainability of other products and processes are much more prevalent and focus mostly on the energy and mobility sectors. Notably, major AI players contribute alarmingly little to sustainability innovation, despite dominating the overall AI market. These findings not only highlight the pivotal role of patents in enhancing our understanding of the field, they also underscore the urgent need for policies that incentivise critical research in sustainable AI. Importantly, this thesis hopes to facilitate future research into the field by providing a hand-labelled dataset and a text-based classifier to distinguish between patents using *AI for Sustainability* and those improving the *Sustainability of AI*. Because one thing is certain: Without effective, evidence-based policy, the current trajectory of sustainable AI innovation gives little indication that the colourful dreams of sustainable AI will come true.

Keywords— Sustainability - Artificial Intelligence - Innovation - Patents - Natural Language Processing

Environmental Disclaimer

As we gain a better understanding of the tremendous environmental costs of AI systems, it is imperative for scholars and practitioners alike to contribute to making AI more sustainable. A crucial first step is to make transparent the computational resources required for training models. This will allow for a better evaluation of whether these costs are justified and how they might be minimised. In the present thesis, the following computational and environmental resources were used.

1. Classification models

Hardware specifications: All classification models were computed on the OII server, using the NVIDIA A100 80GB PCIe GPU.

Training duration: Including experimentation, 343 models were trained with an average runtime of 22.9 minutes, resulting in a total training time of 7844.4 minutes or 130.7 hours.[1]

Energy consumption: In total, the training required 60.74 kWh of energy (estimated with Green Algorithms[2] as recommended by Bouza, Bugeau, and Lannelongue (2023)).

Carbon footprint: This translates to a carbon footprint of 14.04 kg CO2 equivalents (Green Algorithms).

2. Topic models

Hardware specifications: The topic models were also computed on the OII server, using both the NVIDIA A100 80GB PCIe GPU and the Intel Xeon Gold 6338 CPU.

Training duration: Including experimentation, 7 models were trained with an average runtime of 6.2 minutes.

Energy consumption: In total, this required 432.30 Wh of energy (Green Algorithms).

Carbon footprint: This translates to a carbon footprint of 99.91 g CO2 equivalents (Green Algorithms).

[1] Note that the server is used by several people at a time which impacts the training duration. By taking the average runtime, I attempt to provide a reasonable estimate.

[2] https://calculator.green-algorithms.org/

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1 | Introduction

In March, Google researchers published a paper showcasing FloodHub, the company's own Artificial Intelligence (AI) powered flood forecasting system. Using long short-term memory networks, FloodHub outperforms state-of-the-art modelling systems and its accurate and timely warnings promise to save thousands of lives worldwide (Nearing et al., 2024). The initiative is a testament to Google's belief in the "transformative role" (Google, 2023) that AI can play in addressing global challenges, above all the climate crisis. However, Floodhub also exemplifies a broader narrative that is promoted by many major AI companies: the vision of technology as a comprehensive and effective solution to planetary health. This narrative has long since spread. Pointing to projects ranging from waste management to ocean cleanup, experts across industries and politics celebrate AI as the key to sustainability (UNFCCC, 2024; World Economic Forum, 2024).

However, the story does not end there. Google's 2024 environmental report reveals some sobering facts about the sustainability contribution of AI. Over the past five years, the company's emissions have soared by 48% - driven mainly by AI infrastructure (Google, 2024). Similar statistics are being reported across the AI landscape. Training the prominent GPT3 model, for instance, is estimated to have resulted in 552t CO_2 emissions, which is equivalent to 1000 flights from London to New York (Patterson et al., 2021). The water consumption necessary for cooling AI computing infrastructure is similarly concerning. P. Li et al. (2023) estimate that by 2027, the AI sector could account for up to 6.6 billion cubic meters of yearly freshwater consumption - almost two-thirds of the annual consumption of England (Department for Environment, Food and Rural Affairs, 2024). With compute demands of newly released systems doubling every 3-4 months (Amodei and Hernandez, 2018), these figures give rise to a critical question: Can AI truly serve as a solution to the climate crisis, or does it actually risk exacerbating the problem?

This tension between environmental costs and benefits of AI illustrates a crucial insight: To work towards "sustainable AI", i.e., AI that is compatible with environmental sustainability, we must engage with two levers simultaneously. The first lever lies in harnessing *AI for Sustainability*. As realised in projects like Floodhub, this approach leverages the automation and prediction potential of AI systems to unlock progress in climate change mitigation and adaptation. The second lever consists in improving the *Sustainability of AI*, for instance by optimising the energy and freshwater consumption. Only if both aspects receive sufficient attention, that is, only if we effectively use AI to advance climate change mitigation and adaptation while minimising its damaging impact, AI can optimally contribute to our fight against the climate crisis (van Wynsberghe, 2021).

Importantly, this is not bound to happen automatically. Currently, companies and researchers show much more interest in showcasing how AI could save the planet than in reducing the environmental impacts of their models (van Wynsberghe, 2021). To instead guide research and innovation toward a comprehensive understanding of both pillars of sustainable AI, we need transparency about the progress that has been made as well as the gaps that remain. On the one hand, this will enable researchers and developers to identify and focus on the most pressing problems. Oftentimes, however, simply pointing out neglected areas and urging innovators to work on them is not enough. Large AI companies, in particular, may have monetary incentives that conflict with the developments necessary to establish sustainable AI. Thus, transparency is also essential for designing effective policy, steering the AI sector toward sustainable practices and innovation.

While emerging literature discusses the trajectory of sustainable AI research, the analyses rest on example projects and theoretical use cases, falling short of providing actual evidence-based transparency. Moreover, despite the most influential AI players being technology companies, most articles confine their analysis solely to academic research, thereby overlooking important innovation occurring in the industry (Akter, 2024; Rolnick et al., 2019; Stein, 2020; Vinuesa et al., 2020). This thesis sets out to fill this important gap and provide the first large-scale quantitative analysis of sustainable AI inventions. As a novel methodological approach, I propose to use patents as a rich data source, resting the analysis on Natural Language Processing (NLP) techniques. For this, I focus on European patents, analysing on the following research question:

Are patents, analysed using Natural Language Processing (NLP) techniques, a relevant element of inquiry to improve our understanding of innovation within the field of sustainable AI?

The answer to this question will be guided by a collection of subquestions which illuminate different dimensions of sustainable AI innovation. This approach allows me to obtain a nuanced assessment of the scientific value of a patent analysis in the context at hand. The subquestions are as follows:

1. How is innovation activity balanced between the fields of *Sustainability of AI* and *AI for Sustainability*?
2. How are inventions using *AI for Sustainability* clustered across different sectors and technologies?
3. How are inventions that improve the *Sustainability of AI* clustered along the AI pipeline?
4. Which environmental impacts of AI systems do inventions focusing on the *Sustainability of AI* attempt to mitigate?
5. Who are the major actors patenting solutions in sustainable AI?

This thesis makes two critical contributions. Firstly, I provide the first large-scale empirical evaluation of trends and gaps within sustainable AI innovation. The insights generated by this are an essential foundation of policy necessary to align the AI sector with environmental sustainability. Secondly, I aim to facilitate future scientific inquiry into this crucial area by testing NLP-based patent analysis as a novel perspective on innovation in sustainable AI. As part of this project, I present a classifier trained on a new hand-labelled dataset which allows for a differentiation between patents using *AI for Sustainability* and those improving the *Sustainability of AI*. This can be used by other scholars to continue and expand this important line of research. In consequence, the critical contributions made by this paper will hopefully serve as valuable guidance in establishing truly sustainable AI.

The rest of this paper proceeds as follows. In section 2, I will review the theoretical background and motivate my research questions. Section 3 will detail the data selection and retrieval and present the empirical strategy. In section 4, I will present analytical results. After discussing my findings, as well as the strengths and limitations of this paper in section 5, I will offer a conclusion in section 6.

2 | Literature Review and Theoretical Framework

In the following, I review the theoretical background informing this study. First, I discuss how sustainable AI can be conceptualised. Then, I argue that patents are a useful lens through which to analyse innovation in this field: Due to companies' interest in protecting their sustainable AI inventions, patents document a relevant subset of innovation and expand our understanding of progress in sustainable AI beyond academia. Finally, I elaborate on how the subquestions presented above illuminate significant aspects of sustainable AI innovation, allowing me to answer my overarching research question.

2.1 Sustainable AI

This paper is based on a definition of sustainable AI brought forward by van Wynsberghe (2021). In the scope of this thesis, I focus specifically on the environmental dimension of sustainability, which can be defined as "meeting the resource and services needs of current and future generations without compromising the health of the ecosystem" (Morelli, 2013, p. 5). Following van Wynsberghe (2021), I understand sustainable AI as having two pillars: *AI for Sustainability* and *Sustainability of AI* (see Figure 2.1).

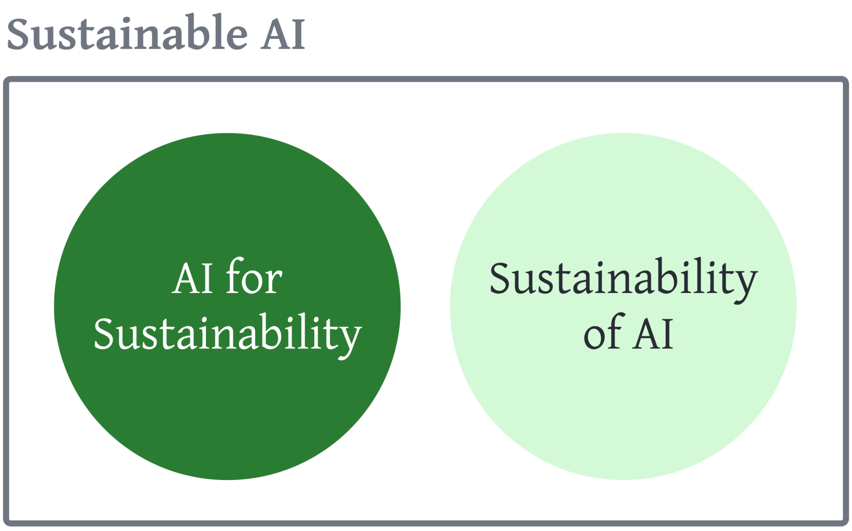


Figure 2.1: Two pillars of sustainable AI

2.1.1 *AI for Sustainability*

On the one hand, sustainable AI includes technologies which apply AI to broadly further sustainability. Coined *AI for Sustainability*, this branch encompasses projects such as the FloodHub initiative discussed in the introduction. In recent years, a range of *AI for Sustainability* inventions has been proposed. The AI for SDGs

ThinkTank even published a designated database covering over 13,500 projects which use AI systems to tackle Sustainable Development Goals (SDGs), with over 1000 projects specifically focusing on Climate Action (AI4SDG Think Tank, 2024). Notably, while many of these initiatives make important contributions to tackling the climate crisis, it is important to acknowledge that influential companies have a vested interest in the narrative of AI as the solution to global challenges. Framing the climate crisis as a technological problem which can be solved with their own products, allows AI players to underscore and strengthen their significance and influence (Morozov, 2013; Nachtwey and Seidl, 2024). As such, it must be carefully evaluated what benefits *AI for Sustainability* projects bring and where they may fall short of actually solving problems. Nonetheless, an analysis by Vinuesa et al. (2020) suggests that *AI for Sustainability* innovation can make a significant contribution. Using a consensus-based expert elicitation process, they estimate that AI may enable the accomplishment of 93% of environmental SDG targets, with particular benefits relating to modelling climate impacts (Word Economic Forum, 2018), improving environmental planning, e.g., by detecting desertification (Mohamadi, Heidarizadi, and Nourollahi, 2016), and optimising energy distribution and usage (Word Economic Forum, 2018).

2.1.2 *Sustainability of AI*

Technologies in the second pillar of sustainable AI focus on making AI itself more sustainable. With AI systems often being portrayed as immaterial and almost inherently sustainable (Kuntsman and Rattle, 2019; Saetra, 2023), this aspect tends to remain overlooked. However, as more and more evidence emerges which quantifies the immense environmental consequences of AI systems, the *Sustainability of AI* is starting to gain scientific attention (Verdecchia, Sallou, and Cruz, 2023). By now, scholars have proposed different soft- and hardware-based approaches to make AI systems less environmentally damaging. Focusing on algorithm optimisation, for instance, structure simplification approaches for deep neural networks have been shown to enable up to 115% energy savings (Zhang, Davoodi, and Hu, 2018). Importantly, research in this field is set to become all the more relevant as AI is being integrated into societal and business infrastructure: currently estimated at $196.6 billion, the global AI market is projected to reach a size of over $1.7 trillion by 2030 (Grand View Research, 2024a). The consequences of this development are serious: The global electricity consumption of data centres rose from 204 TWh in 2018 to 460 TWh in 2022 (International Energy Agency, 2024; Masanet et al., 2020). By 2026, even under conservative assumptions, this is expected to increase to as much as 800 TWh, i.e. almost quadrupling the electricity consumption within 8 years (International Energy Agency, 2024). In light of this growth in market size and energy consumption, improving the *Sustainability of AI* becomes a key lever in preventing severe environmental damages.

2.1.3 Previous work

Research which analyses the development of sustainable AI is still in the beginning stages. So far, most studies focus on just one of the pillars, studying either the environmental damages resulting from AI models or mapping out their (potential) sustainability applications (Akter, 2024; Gunderson, Petersen, and Stuart, 2018; Rolnick et al., 2019; Stein, 2020; Vinuesa et al., 2020). Importantly, this often paints a one-sided picture by overestimating the positive impact of AI while ignoring the costs or only considering the environmental harms without acknowledging potential benefits. Only a handful of studies have provided a more comprehensive overview, carefully discussing the relationship between risks and benefits (Cowls et al., 2021; Khakurel et al., 2018; Tomasev et al., 2020).

Problematically, the literature so far relies on theoretical analyses and exemplary projects. However, especially when providing the policy guidance required for steering innovation in the right direction, it is imperative to obtain large-scale empirical evidence (Kaack et al., 2020). Moreover, studies in sustainable AI exhibit a strong focus on academic research, with industry developments remaining overlooked. However, as I will argue, companies present a relevant arena of innovation. Not only are they positioned at the forefront of AI development, but they also generate important insights about the practical implementation and scalability of AI solutions in real-world scenarios (Fan, Yan, and Wen, 2023). Confining insights to academic literature is therefore insufficient for capturing all relevant innovation in the field. To fill this gap, I propose to use patents as a large-scale data source on innovation in sustainable AI.

Notably, Verendel (2023) uses a similar approach when analysing AI in climate inventions using US patent data. However, while this constitutes an interesting first step, the paper only considers higher-level bibliometric patterns, without investigating innovation activity itself. Furthermore, the study does not offer a theory-led analysis: it investigates sustainable AI as one large area without distinguishing between the two pillars. As such, it cannot indicate whether different aspects are sufficiently addressed and to what extent further research needs to be incentivised. By improving on their work, this thesis will, to the best of my knowledge, provide the first large-scale analysis of innovation activity within sustainable AI.

2.2 Innovation in sustainable AI

To strengthen the case for patents as a data-source and framework, I will now detail why companies engage in significant sustainable AI innovation and why they use patents to protect these inventions.

Research suggests that companies have strong economic reasons to be involved in sustainability innovation in general. Most importantly, inventing more sustainable products and processes, such as more eco-friendly business models or production methods (Adams et al., 2016; G. Li et al., 2019), come with two perks. For one, eco-friendly operations can directly reduce costs by minimizing resource usage and waste (Hermundsdottir and Aspelund, 2021; Ram Nidumolu, 2009). However, as the climate crisis is increasingly recognised as one of the most pressing challenges to overcome, sustainability also emerges as a powerful instrument to boost a company's reputation. Marketing one's firm and products as environmentally friendly can gain the support and trust of stakeholders and thus improve market status and popularity (Gomez-Trujillo, Velez-Ocampo, and Gonzalez-Perez, 2020; G. Li et al., 2019). While many companies thus relevantly engage in sustainable innovation, it is important to note, that strong incentives to be perceived as eco-friendly do not necessarily lead to genuine sustainability efforts. Instead, some inventions may be "greenwashing" attempts, although this is often difficult to discern in quantitative data (Z. Yang et al., 2020).

Companies engage in sustainable AI innovation, in particular, for at least two distinct reasons. For one, it allows AI companies to expand their societal influence. As discussed, framing the climate crisis as a technological problem to which AI systems present the solution, allows AI suppliers to position themselves as relevant for society and thus gain support and power (Morozov, 2013; Nachtwey and Seidl, 2024). Most effectively, this narrative can be maintained by presenting inventions such as FloodHub, which impressively showcase the potential AI holds to address the climate crisis. *AI for Sustainability* innovation can therefore be leveraged to associate AI as a sector with sustainable goals. Engaging in selected innovation concerning the *Sustainability of AI* can then create a synergy: it strengthens the notion that a firm is seriously committed to reducing their environmental impact while feeding into the idea of AI as a sustainable (and therefore valuable) technology.

A range of tech companies follow this strategy. Google, for instance, have developed a range of climate-smart technologies, including the Environmental Insights Explorer, a data-based tool aiming to help policymakers reduce emissions (Mendes, 2023, pp. 191-194). These showcase the potential of using *AI for Sustainability*. Additionally, Google innovates the *Sustainability of AI* and prominently features such inventions in their external communication. For instance, in their 2022 report on "Accelerating Climate Action at Google and Beyond", the company presented a machine-learning-optimised Tensor Processing Unit (TPU) which claims to generate 93% fewer emissions compared to similar unoptimised servers (Google and Boston Consulting Group, 2023). Similar patterns can be observed across other large AI players including Microsoft, Meta, Amazon (Mendes, 2023, pp. 2017-224), and NVIDIA (NVIDIA, 2022).

Companies without a core AI business have a different incentive to produce sustainable AI inventions. For them, using AI can facilitate the transformation toward more eco-friendly operations which, as discussed, comes with monetary and reputational perks. Monetary benefits can often be captured by integrating AI into firm internal processes such as production, for instance by using smart manufacturing and maintenance to improve energy efficiency (Bokrantz et al., 2020; Mittal et al., 2020). Using AI in actual products, on the other hand, often comes with reputational benefits. If products are more sustainable than those of competitors, for instance by using AI based monitoring to improve efficiency and resource utilisation Liu et al. (2022), this allows for a differentiation of the firm which in turn can boost reputation and lead to superior market status (G. Li et al., 2019). Often, AI is integrated both in firm-internal processes as well as products. For instance, when looking at the energy sector, AI is used for data-driven and efficient demand forecasting and energy management, i.e., provider-level processes, as well as in actual products such as smart meters (Aslam et al., 2021; Menghi et al., 2019; Wang et al., 2019).

Both dynamics present strong incentives for firms to engage in sustainable AI innovation, speaking for the idea that significant sustainable AI innovation is indeed generated within the industry context. Note, however, that this does not mean that companies necessarily have a genuine commitment to climate justice. Many of these firms contribute massively to global emissions and their "green innovations" are largely motivated by monetary incentives (Mendes, 2023, pp. 188-224).

2.3 Patents as a framework of innovation

To study firms' sustainable AI innovation activity, I argue that patents are a highly useful data source. Patents are exclusive rights over an invention and constitute one of the most common forms of intellectual property protection (IPP) (Azzam, 2009). They allow innovators to prevent others from commercially using, producing, or distributing their invention, usually for a limited time period (Pila, 2019, pp. 99-101). To patent a technology, inventors must submit an application to a national or international patent office, such as the European Patent Office (EPO), detailing their invention and a set of claims, i.e., boundaries within which the technology is protected (Pila, 2019, pp. 102-103).

It is important to note that there are some limitations to what can be patented, especially for immaterial goods such as AI. In the jurisdiction of the EPO, AI is patentable as long as it has a proven "technical character". In theory, this means that inventions must have physical features or use some form of technical means. However, this entails a very wide definition: a technical character can be proven by simply applying an algorithm to some technological context, even if it is as general as classifying image or audio data, or by solving a technical problem related to AI (EPO, 2024a). Specifically when looking at AI in the context of sustainability, most technologies in both pillars clearly fall under this criterion: In the field of *AI for Sustainability*, AI is by definition applied to a specific context, for which it aims to further sustainability. Within *Sustainability of AI*, solutions tend to incorporate some form of technical implementation of an AI model which allows an algorithm to become less environmentally damaging.

Notably, AI is not only theoretically patentable, research also suggests that technology companies show immense interest in using patents to protect their inventions, for at least three reasons. Firstly, large technology players strategically use intellectual property rights to strengthen and preserve their innovation leadership. According to Rikap (2023), tech companies create "Data-driven Intellectual Monopolies". This phenomenon describes monopolistic market structures that are based on ownership over knowledge: exclusive access to innovative AI systems combined with ownership of data and computing infrastructure allows firms to benefit from the network complementarities of controlling the entire AI value chain. A crucial aspect of maintaining this control is to engage in continuous innovation to ensure intellectual leadership and prevent potential competitors from catching up. In this system, patents are a way of appropriating and gatekeeping research, including research which is done in cooperation with academic institutions, and thus gaining exclusive access to the most advanced AI systems. Microsoft exemplifies this business strategy. Over the past 10 years, the company has engaged in continuous innovation across their mobile and cloud business to preserve and expand their status as a data-driven intellectual monopoly (Ibarra and Rattan, 2018). As a result, Microsoft has built the second-largest AI patent portfolio in the world, only exceeded by IBM (WIPO, 2019).

With these growing power structures around knowledge, patenting becomes also a protective strategy. Powerful companies' aggressive patenting strategies create a constant threat of patent disputes, potentially involving highly expensive litigation. This forces especially smaller firms to also build up patent portfolios in order to improve their negotiating position or to be able to credibly threaten a counterclaim if necessary (Noel and Schankerman, 2013). It even makes it worthwhile for companies to patent technologies if otherwise, it would not be. Patenting is expensive, complex and time-consuming. Especially for fast-moving technological fields such as AI, where independent discovery or reverse engineering by competitors is unlikely, innovators may prefer more flexible forms of IPP. For instance, firms may use trade secrecy (La Diega, 2018; Meyers, 2018) or forego protection altogether and share software with the open-source community. But given this specific background, many AI developers follow a dual strategy where their code is open-sourced and shared with the academic community while also being protected with a patent. Open-sourcing their products allows companies to build a reputation and attract talent from top research institutions, while patent portfolios protect the firm (Calvin and Leung, 2020; Hutson, 2023).

A third dimension contributing to the high relevance of patents in the context of sustainable AI is the fact that, increasingly, AI is embedded in hardware products and machinery. Particularly *AI for Sustainability* inventions such as the battery and energy examples discussed above are often applied to technological fields which are less fast-moving and where reverse engineering is indeed a problem (Bessen and Hunt, 2007; Comino, Manenti, and Thumm, 2019). Naturally, these sectors are much more interested in using patents as a protection mechanism. This is all the more true since in recent years, the tangible entry barriers to many technology markets have fallen. AI systems, in particular, can now be applied easily even by firms with relatively little expertise, such that IPP becomes more important to protect inventions (Gereffi, 2014).

Overall, this makes a strong case for the relevance of studying sustainable AI through the lens of patents. Nonetheless, it must be acknowledged that patents do not cover all relevant inventions. To the best of my knowledge, the share of non-patented AI technologies is unknown. But as the arguments above show, patenting dynamics are determined by strong and complex incentives, such that findings are likely not fully generalisable to non-patented technologies.

2.4 Research questions

Following this argumentation, I empirically evaluate patents as a data source of sustainable AI innovation. Patents contain a wide range of information about a technology. For instance, extensive textual data describes the functionality and application of an invention and bibliometric information details citations and connections between patents (see Figure 2.2).

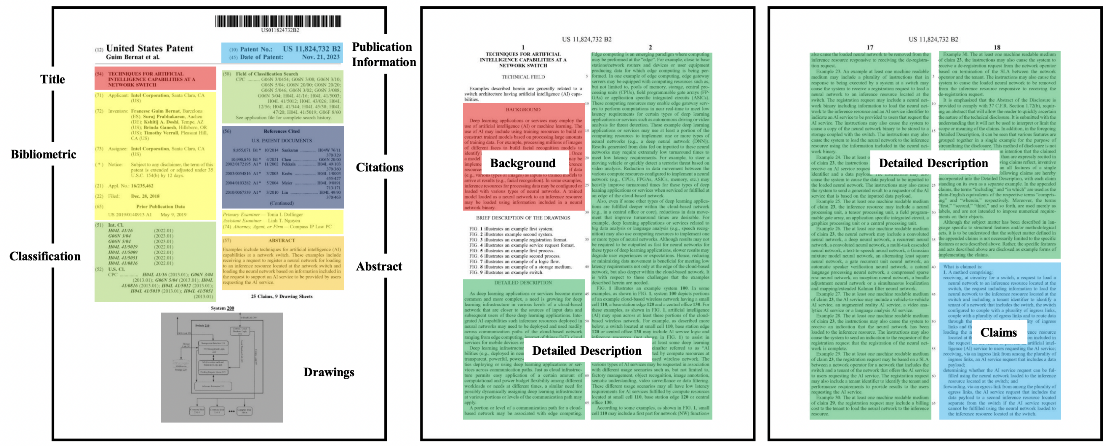


Figure 2.2: Example of a patent layout detailing the different elements of patent publications (visualisation by Jiang and Goetz (2024))

I propose to specifically focus on textual elements in the patent data. So far, many patent-based studies concentrate on the bibliometric data, analysing, for instance, a patent's novelty (Dahlin and Behrens, 2005) or forecasting technology developments (Daim et al., 2006). Another strand of studies uses patent classification codes which are assigned by patent offices and contain information about the type and technological domain of a patent. Papers in this branch include technological trend analyses and patent valuation assessments (Jeon, Chae, and Gim, 2020; G.-C. Yang et al., 2015). Both approaches, I argue, are somewhat limited in extracting useful information about sustainable AI innovation. Bibliometric information can only illuminate relationships between patents without focusing on content. While classification codes do contain information about a patent's content, they are limited in providing a comprehensive and unbiased overview. Since classification systems are developed by human experts, they impose human judgements about which categories are relevant and how they relate to each other. This pre-determines which types of innovations can be identified - if a category does not have a designated code, it cannot be found. This is particularly problematic in fast-moving fields like AI, where the classification systems may lack many new and significant categories and thus obscure important innovation patterns. Analysing textual data with NLP techniques, instead, allows for a data-driven analysis, giving potentially more comprehensive insights and reducing this bias. Since NLP techniques cover a wide range of applications, including patent classification and content retrieval (Jiang and Goetz, 2024), they provide a promising approach to the analysis of sustainable AI patents. This informs my overarching research question (RQ):

RQ: Are patents, analysed using NLP techniques, a relevant element of inquiry to improve our understanding of innovation within the field of sustainable AI?

To answer this research question, I analyse five subquestions (SQ). Each one, I argue, illuminates a relevant element of sustainable AI innovation. Combined, they will make evident whether and how a patent perspective enriches our understanding of the field. The first subquestion concerns the balance between innovation in *AI for Sustainability* and *Sustainability of AI*, the two pillars of sustainable AI. While van Wynsberghe (2021) clarifies that both branches are valuable and necessary components of achieving truly sustainable AI, this view is not mirrored in the general discourse on AI. As discussed, AI is oftentimes strategically portrayed as the (sole) solution to global challenges such as the climate crisis (Nachtwey and Seidl, 2024). At the same time, the environmental degradation caused by AI tends to be overlooked or underestimated (Saetra, 2023). This narrative could powerfully impact innovation efforts and lead to large blindspots in the innovation landscape, motivating the first subquestion:

SQ 1: How is innovation activity balanced between the fields of *Sustainability of AI* and *AI for Sustainability*?

A second essential aspect of enhancing our understanding of sustainable AI innovation is to look at the two pillars individually, starting with *AI for Sustainability*. As discussed earlier, inventions in this field apply AI systems to improve production processes, products, and infrastructure. As Fan, Yan, and Wen (2023) find, these applications come with different opportunities and challenges based on the industry sector they are applied to. Analysing the innovation in *AI for Sustainability* by sector and technology group can thus give valuable insights to guide and regulate the use of AI for sustainability purposes in a constructive and effective way. This informs the second subquestion:

SQ 2: How are inventions using *AI for Sustainability* clustered across different sectors and technologies?

When analysing research progress in *Sustainability of AI*, it is common practice to conceptualise innovation along the AI development process, i.e., organising innovation by the experimentation, training and inference phases of AI models (Chien et al., 2023; Patterson et al., 2021). When applying a patent lens, this conceptualisation has limited applicability. After all, the same hardware implementations, e.g., GPUs, can be used for all of these phases. Instead, I follow Wu et al. (2022) in their framework of the areas of optimisation along the AI pipeline (see Figure 2.3). According to this framework, the AI pipeline consists of data collection on the one hand and AI operations on the other hand. Within the latter, optimisation can be achieved by innovating

- platforms, i.e., frameworks or suite of tools providing the necessary software infrastructure and interfaces for using AI models,
- models, i.e., specific model architectures,
- specialised AI hardware, for instance, hardware accelerators such as GPUs, or
- infrastructure, i.e., components related to network connectivity, data and model storage, and general hardware such as cooling or power supply.

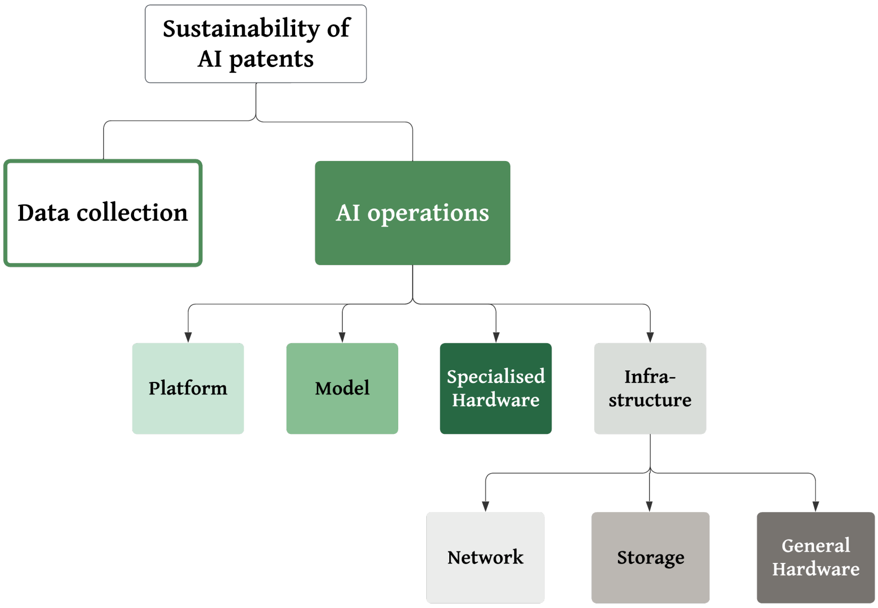


Figure 2.3: Overview of areas of optimisation along the AI pipeline

Based on this conceptualisation, I study the following third subquestion:

SQ 3: How are inventions that improve the *Sustainability of AI* clustered along the AI pipeline?

The fourth subquestion relates to the specific sustainability dimensions targeted by innovations. For this, I only consider *Sustainability of AI* inventions, as these are bound to target the specific environmental impacts of AI systems.[1] Major impacts suggested by the literature include energy consumption, water consumption, waste and resource depletion, particularly rare metals which are crucial for many hardware components (Ligozat et al., 2022). Since arguably, all impacts should be reduced to

[1] *AI for Sustainability* inventions, on the other hand, could contribute to sustainability in many more ways, for instance by improving the performance of some inherently "sustainable" technology (e.g., smart grids) or by predicting environmental and climate dynamics. The environmental impact analysis here is highly complex, beyond the scope of this thesis.

make AI truly sustainable, environmental impact analysis can highlight important fields of progress or neglect. This motivates the fourth subquestion:

SQ 4: Which environmental impacts of AI systems do inventions focusing on the *Sustainability of AI* attempt to mitigate

Finally, looking at sustainable AI through the lens of patents allows me to analyse major actors in the patent landscape. These are relevant in two ways. Firstly, with innovation being a key lever of progress in sustainable AI, patents capture to what extent large AI players and other companies show commitment to aligning AI with sustainability. Secondly, patents reveal who owns inventions and thus who benefits from this progress. With innovation being strategically used to expand market power (see Sections 2.2 and 2.3), it is imperative to make transparent who has exclusive access to knowledge.

SQ 5: Who are the major actors patenting solutions in sustainable AI?

Taken together, these five subquestions allow me to reveal whether and how patents can serve as a relevant element of inquiry to improve our understanding of innovation within the field of sustainable AI.

3 | Methodology

In the following, I present my data and methodology. After motivating European patents as the focus of my thesis, I detail how sustainable AI patents were identified and retrieved. I then outline my methodology, presenting a classifier to distinguish between innovation in the two pillars of sustainable AI which is based on a new, hand-labelled dataset, as well as two topic models used for content analysis.

3.1 European patents

I focus on patents published with the European Patent Office (EPO) for two main reasons. Firstly, the majority of research in (Sustainable) AI focuses on the USA, the largest AI market worldwide (Grand View Research, 2023). However, to gain a thorough understanding of sector developments, it is crucial to study a variety of regions. With AI spending projected to reach $66.4 billion in 2024, Europe captures almost a quarter of the global AI market (Grand View Research, 2024b), making it a highly relevant regional focus. Secondly, this thesis aims to generate policy-informing insights necessary to establish sustainable AI. European institutions have already demonstrated a strong interest in building regulatory frameworks for the AI sector (Veale and Borgesius, 2021). Thus, my findings "fall on fertile ground", making it more likely that they can contribute to shaping effective policies which may serve as an example to other regions, including the US, where regulatory attention remains highly fragmented.

How generalisable are findings obtained in Europe? First, it must be noted that firms from all around the world can apply for European patents if they are interested in exclusive ownership over their invention in the European jurisdiction. Thus, my data cover inventions from a wide range of companies worldwide. Naturally, however, the decision to apply for patents in a jurisdiction is guided by specific incentives, such as the market size for a product. Also, not all companies have the required resources to apply for international patents. Entire geographies such as lower and middle income countries may be underrepresented such that European data are likely not generalisable to the full international community. A second aspect potentially limiting the external validity is that patent laws are country specific. Subtle differences between the legislations may impact patterns in the patenting activity, particularly for new and emerging fields such as AI (Pila, 2019). While this project should therefore be considered a case study, European Patents remain a highly interesting context.

3.2 Data

3.2.1 Patent identification

To identify innovation in sustainable AI, I selected patents that lie at the intersection between AI and environmental sustainability. This approach was proposed by

Verendel (2023) in their study on citation patterns of climate AI inventions and successfully captures patents with relevant AI elements.

Patents which relate to AI or sustainability can be identified with "search strategies" developed by major patent organisations. These strategies rely on the extensive classification systems used by patent offices to organise patents. One prominent system is the Cooperative Patent Classification (CPC). Using designated codes, this system categorises technologies into a detailed structure of over 200,000 groups. For example, a patent for a new method of processing neural networks (publication number: EP3839831A1) is classified under "computing arrangements based on biological models" (see Figure 3.1). A similar system is the International Patent Classification (IPC). Both IPC and CPC codes were used in this study.

Classification symbol	Title and description
G	PHYSICS INSTRUMENTS
G06	COMPUTING; CALCULATING OR COUNTING
G06N	COMPUTING ARRANGEMENTS BASED ON SPECIFIC COMPUTATIONAL MODELS
G06N 3/00	Computing arrangements based on biological models
G06N 3/02	• Neural networks
G06N 3/04	• • Architecture, e.g. interconnection topology
G06N 3/048	• • • Activation functions

Figure 3.1: CPC classification scheme example

Specific codes determine whether a patent belongs to a particular technology group, allowing for the selection of relevant patents. For both AI and sustainability, several search strategies exist which have been shown yield different sets of relevant patents (Favot et al., 2023). I thus combine multiple search strategies for a comprehensive overview. Figure 3.2) presents the search strategies used for identifying AI and sustainability patents.

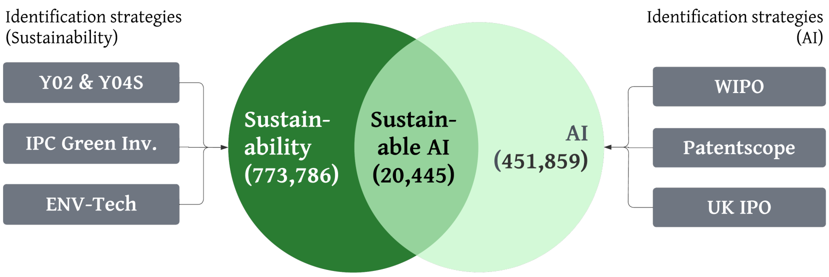


Figure 3.2: Overview of search strategies for obtaining AI and sustainability patents

For detecting AI, I combined three strategies. Firstly, I used the approach provided by the World Intellectual Property Organisation (WIPO), which is most prominent in the literature. The organisation defines AI systems as "learning systems; that is, machines that can become better at a task typically performed by humans with limited or no human intervention"(WIPO, 2019, p. 19). To operationalise this in the context of patents, the WIPO refers to the Association for Computing Machinery (ACM) Computing Classification Scheme, which conceptualises AI as

- AI techniques, i.e., "advanced forms of statistical and mathematical models",
- AI functional applications, i.e., specific functions realized using AI techniques, and
- AI application fields, i.e., larger areas where AI techniques and functional applications can find application (WIPO, 2019, p. 25).

Patents that fall under this definition were detected using CPC and IPC codes, as well as keywords. As the second and third strategy, I use the approaches provided by Patentscope as well as the UK Intellectual Property Office (UK IPO). Both constitute updated versions of the original WIPO strategy and use the same definition of AI.[1][2][3]

For sustainability related technologies, I also combined three strategies. The first group of sustainability patents was identified using the Y02 and Y04S classes in the CPC scheme. These classes were included post-hoc to flag technologies that "control, reduce or prevent greenhouse gas (GHG) emission of anthropogenic origin" (Veefkind et al., 2012). The second group of patents was identified using the IPC Green Inventory proposed by the WIPO in collaboration with the United Nations Framework Convention on Climate Change (UNFCCC) and the Intergovernmental Panel on Climate Change (IPCC) (WIPO, 2010). Finally, the ENV-TECH search strategy proposed by the OECD (Hascic and Migotto, 2015) was applied. All three strategies were developed independently using expert commissions. Notably, no definitions of sustainability or clear conceptual frameworks were published based on which this was done (Favot et al., 2023; Veefkind et al., 2012).

Note, that defining patents as "sustainable" is subject to a critical limitation. Since patents cannot account for the specific contexts within which patented technologies will be produced and distributed, they offer limited information about the environmental damages potentially connected to a technology. Thus, any "sustainability" label of patents can only be an approximation, falling short of a comprehensive assessment.

3.2.2 Patent retrieval

Based on the above identification strategies, I used PATSTAT (Figure 3.3), an online patent database curated by the EPO (EPO, 2024b), to identify publication numbers of relevant patents. Then, textual and bibliographic data were obtained from the

[1] WIPO: https://www.wipo.int/export/sites/www/tech_trends/en/docs/techtrends_ai_methodology.pdf, accessed 20.06.2024.

[2] Patentscope: https://www.wipo.int/tech_trends/en/artificial_intelligence/patentscope.html, accessed 20.06.2024.

[3] UK IPO: https://assets.publishing.service.gov.uk/media/5d2dc787ed915d2fe1abfabe/Artificial_Intelligence_-_A_worldwide_overview_of_AI_patents.pdf, accessed 20.06.2024.

EPO Open Patent Service via their API client. Assignee names and filing dates were taken from Google Patents.[4]

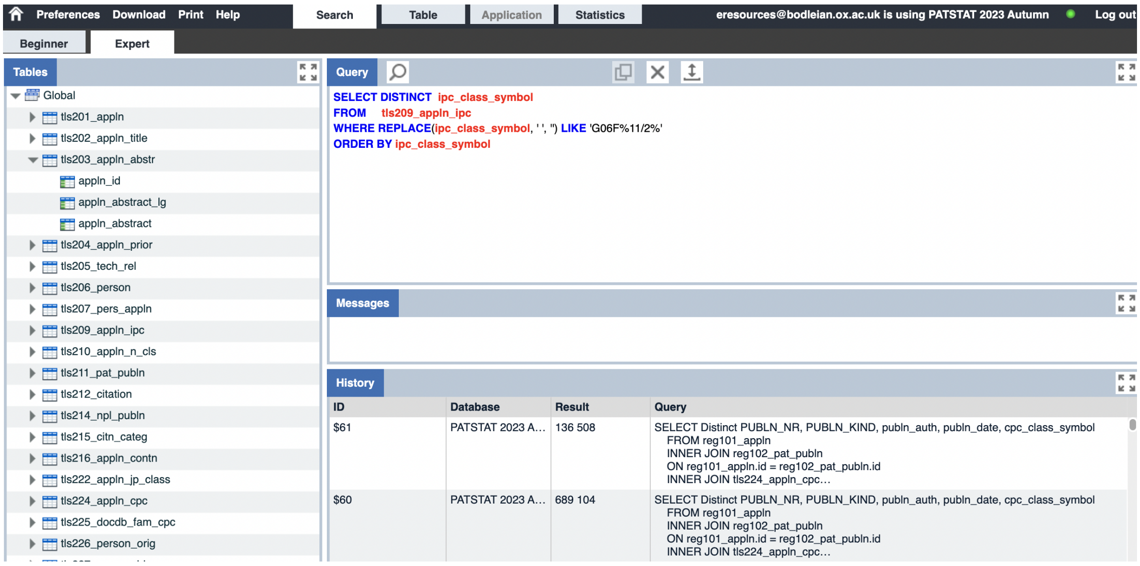


Figure 3.3: Screenshot of Patstat database used for patent retrieval

With this approach, I identified 451,859 AI patents and 773,786 sustainability patents. In the overlap and after deduplication (see Section 3.3.1 below), this resulted in a dataset of 20,445 sustainable AI patents. Figure 3.4 displays these patents over publication years. Notably, annual publication numbers rose substantially over the study period, increasing more than 8-fold between 2000 and 2023.

3.3 Model pipeline

The patent analysis conducted in this thesis consists of two main parts. In the first step, I build a patent classifier, finetuned to differentiating between patents relating to *AI for Sustainability* and *Sustainability of AI*. In the second step, I use topic modelling to analyse which technologies are patented in the two branches.

3.3.1 Data cleaning

Prior to implementing any models, several cleaning steps were undertaken as visualised in Figure 3.5. First, patents, for which no English version of the abstract, description or claims was available, were machine translated using Google Translator. Then, patents were thoroughly deduplicated, a step which is particularly

[4] EPO Open Patent Service API client: https://pypi.org/project/python-epo-ops-client/, Google patents: bulk data were obtained from https://console.cloud.google.com/bigquery?project=axial-gist-422710-c6&ws=!1m12!1m4!4m3!1spatents-public-data!2spatents!3spublications_202310!1m6!12m5!1m3!1saxial-gist-422710-c6!2seurope-west2!3scdd4d719-90e4-46af-b42e-48e6a1a1b60f!2e2 and missing patents were queried directly on the website https://patents.google.com/, all accessed 20.06.2024.

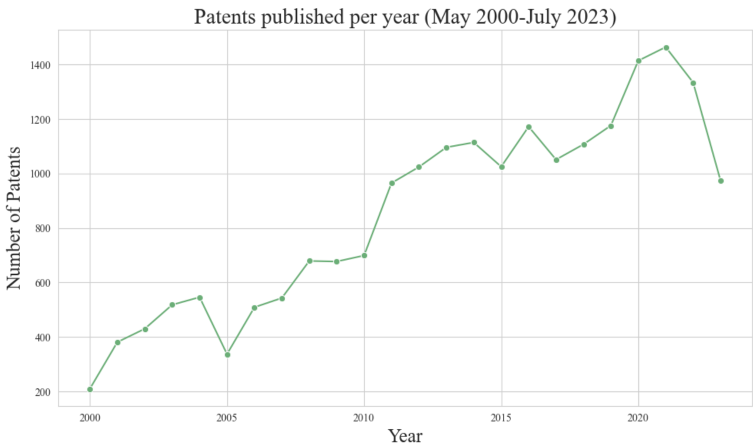


Figure 3.4: Yearly sustainable AI patent publications between 2000 and 2023

important for NLP tasks where it has been shown to improve model performance (Lee et al., 2022). For patents which share the publication number, country and title, I kept only that patent in the dataset, which exhibits the most textual data components (i.e., abstract, description and claims). This is assumed to maximise the information contained about a patented technology.

As discussed above, patents were retrieved from several different data sources. Each platform provides patents with titles, so each patent can have multiple titles that may conflict with each other. To consolidate this, patents with conflicting information were filtered and cross-checked manually. For 1,386 patents, titles from Google and EPO showed some discrepancy. In these cases, the longer title was chosen, assuming that this would capture more information about the patent. Finally, all texts were set to lower case and patent specific elements such as references to drawings were removed. Since I used transformer models later in the analysis, no stopwords were removed.

3.3.2 Hand labelling

To train a classifier that can differentiate between the two pillars of sustainable AI, I required ground truth data. Notably, this study is the first to empirically analyse sustainable AI conceptualised as consisting of two branches. Ergo, no labelled datasets existed (yet) that could be used for this purpose. Instead, I manually labelled patents as concerning *Sustainability of AI* and/or *AI for Sustainability*. I used the following inclusion and exclusion criteria.

For technologies to be labelled as concerning the *Sustainability of AI*, they must relate to the AI pipeline as proposed by Wu et al. (2022). As discussed, this includes technologies relating to data collection and AI operations, i.e., platforms, models, specialised AI hardware and infrastructure. Patents concerning energy production and grids were excluded. While more sustainable energy systems do contribute to reducing the environmental impact of AI, such patents were considered not sufficiently specific to AI. For technologies to be labelled as concerning *AI for Sustainability*,

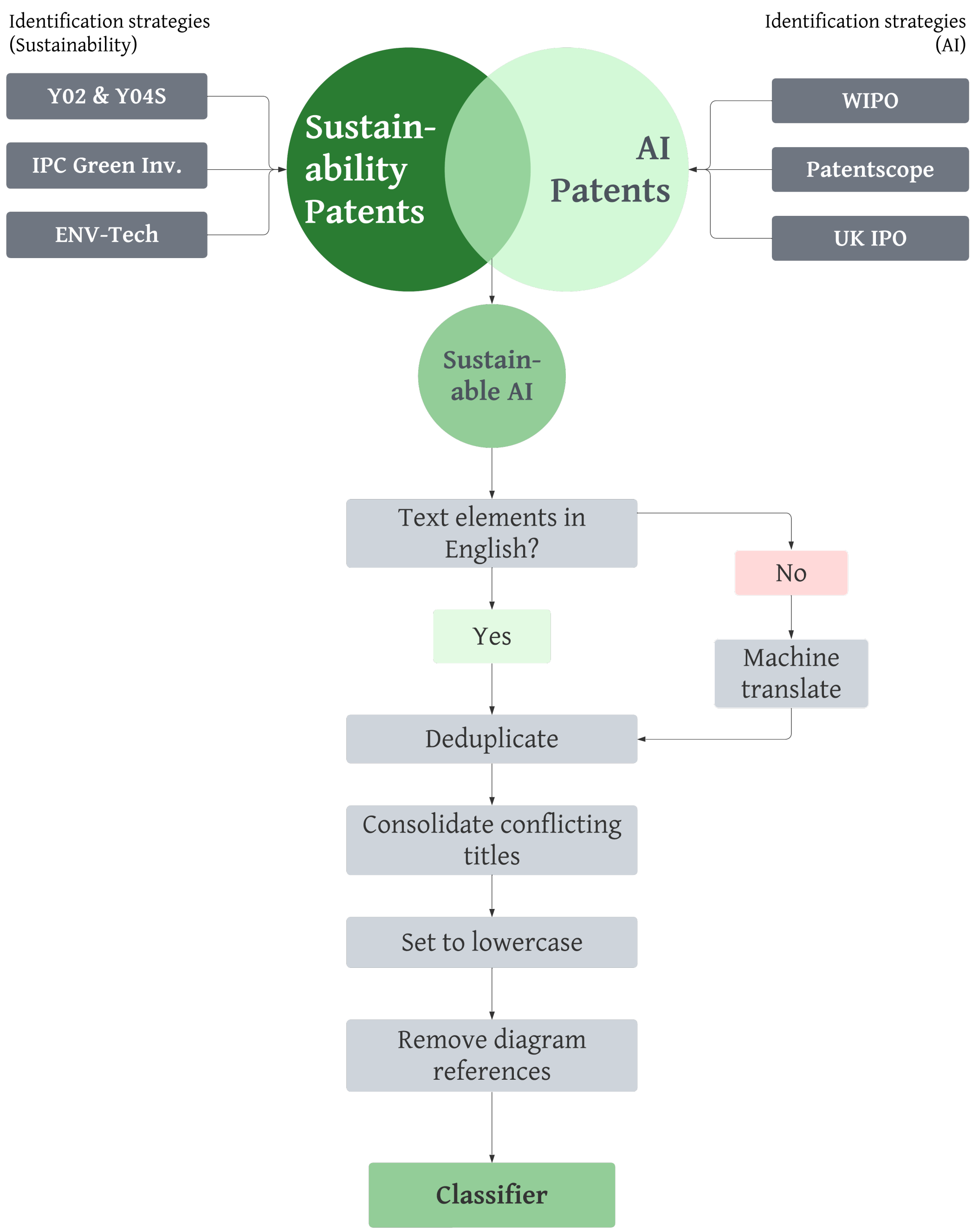


Figure 3.5: Flowchart of data retrieval and cleaning

they must use AI to make another process more sustainable and/or provide information necessary to achieve this.

Importantly, some technologies were labelled as concerning both classes. For instance, automated power factor correction, a method for compensating for lagging current, is an AI-related product that is used to improve the sustainability of data centres (i.e., AI pipeline) and other products (Zhu et al., 2023). Similarly, some patents were falsely included in the group of sustainable AI patents. For instance, some patents related to brain surgery, potentially included via neural network related keywords. Such patents were labelled as belonging to neither class.

For the hand labelling, I adopted a three-stage process. First, a random sample of 500 patents was drawn. However, this resulted in an extreme under-representation of patents in the *Sustainability of AI* class, with less than 20 sample patents. Since a classifier can likely not extrapolate from such few samples to the wider group, I secondly used keyword-searches to obtain more minority-class patents. For this, I designed queries using keywords along the AI pipeline, aiming to capture *Sustainability of AI* patents which are as broad and diverse as possible (see Appendix A for keyword list). In this stage, an additional 200 patents were labelled. Despite the careful design of keyword searches, this likely resulted in a biased training set, where only specific types of *Sustainability of AI* inventions are included. Problematically, the classifier may not be able to extrapolate to all types of patents in that class, such that the performance on the training set may be misleadingly high compared to the performance on all unlabelled data.

To circumvent this issue, I adopted an Active Learning (AL) approach as the third stage. Designed for contexts where labelled data is scarce and costly to obtain, AL is a method to strategically select those instances which would be most informative to label. Thus, it aims to maximise the information value of the training set, enabling the classifier to reach better performance on unseen data compared to random or biased sampling (Tharwat and Schenck, 2023). AL has been tested specifically for BERT-based models with highly promising results (Ein-Dor et al., 2020), making it an excellent method for this study.

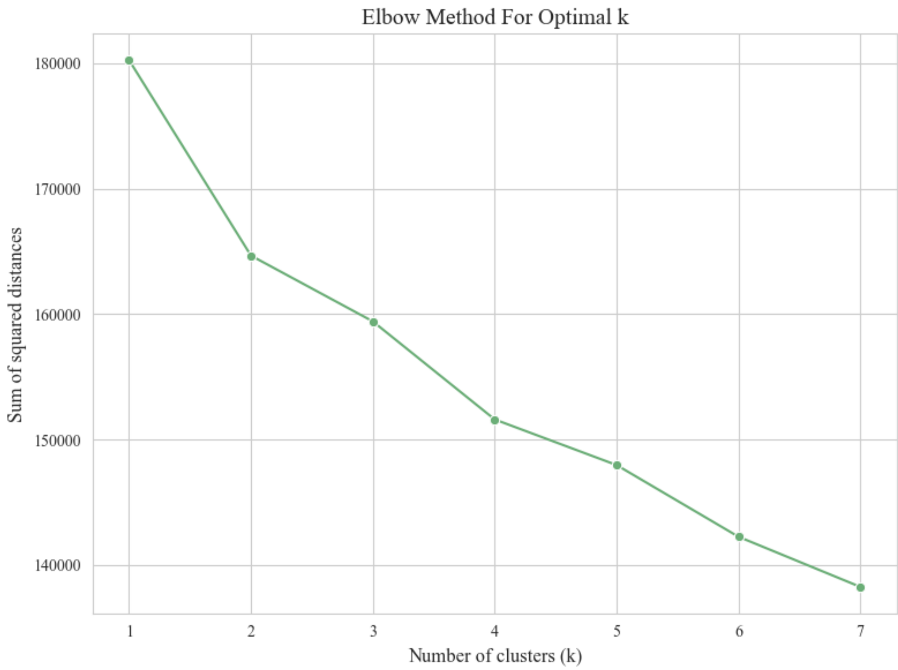
To implement AL, one first trains the classification model, on the small sample of initially labelled instances. Here, I trained a baseline BERT model (see Section 3.3.4). Then, this model is used to predict classes for all unlabelled patents in the dataset. To identify the most informative instances, I used the least confidence strategy proposed by Lewis (1995). For each prediction, this method takes the probability distribution over all possible classes and computes the entropy which is a measure of uncertainty. It selects those predictions with the highest entropy (i.e., the predictions where the model is least certain about the label) for manual validation. In this third stage, 300 patents were labelled, resulting in a final training dataset of 1000 patents. The label distribution in this training set is presented in Table 3.1.

Patent Label	Training set	Test set	All labelled data
AI for Sustainability	594	150	744
Sustainability of AI	97	21	118
Both	102	29	131
None	7	0	7
Total	**800**	**200**	**1,000**

Table 3.1: Counts of patent labels

3.3.3 Label validation

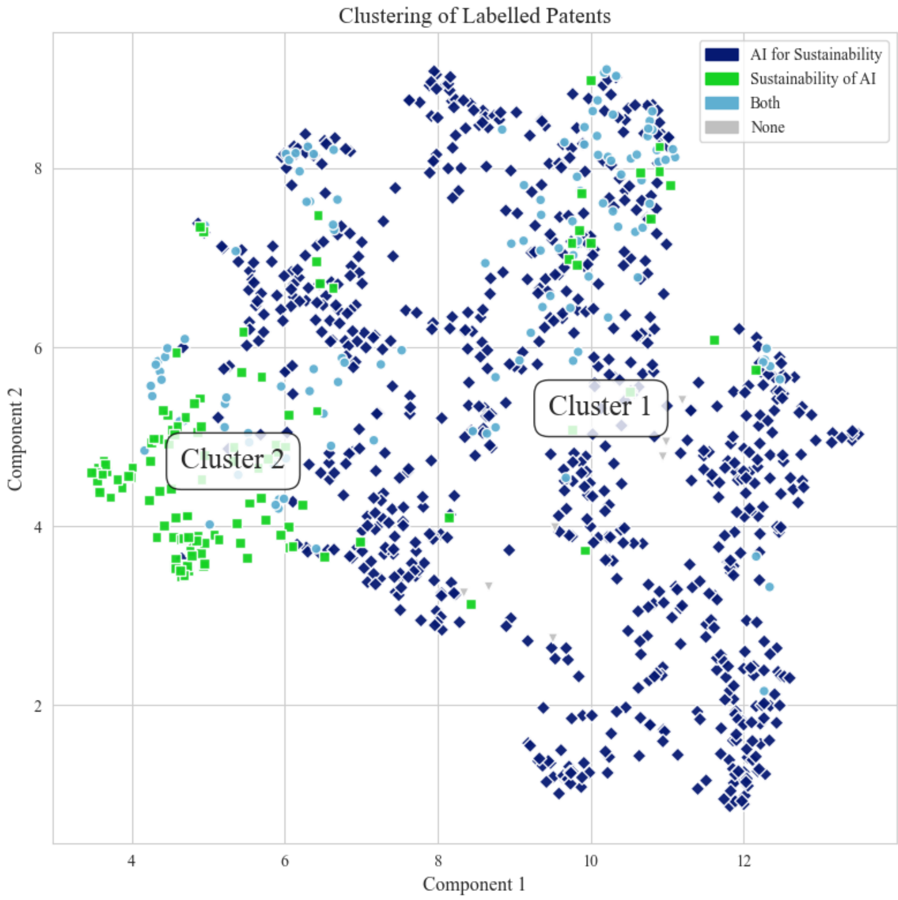
Clustering the labelled patents using K-means showed that patents with the same label are indeed clustered together, validating this strategy. The number of clusters was checked using an elbow plot (Figure 3.6). Although there is not one clear elbow, the plot indicates that two clusters fit well.



Elbow plot visualising the sum of squared distances between data points and their corresponding cluster centroids for different values of K. The elbow method was used to determine the optimal K in the K-means clustering of patent embeddings.

Figure 3.6: Elbow plot for K-means clustering

Figure 3.7 shows a Uniform Manifold Approximation and Projection (UMAP) (McInnes, Healy, and Melville, 2020) visualisation of the clustering. To check how well the projection preserves the data structure, I calculated trustworthiness. This metric expresses how much of the original rank order of data points' K nearest neighbours is preserved in the low-dimensional space (Stasis, Stables, and Hockman, 2016). With scores of above 0.9 for up to K=50 nearest neighbours, the projection is indicated to be a good representation of the original dataset.



UMAP visualisation of K-means Clustering of labelled patents.

Figure 3.7: Clustering of labelled patents

The cluster centres neatly align with the two sustainable AI pillars. Notably, *Sustainability of AI* patents are much more condensed than *AI for Sustainability* patents. This, however, makes sense given that the former are focused on technologies relating to the AI pipeline only, while the latter apply AI to a wide range of different contexts, explaining the wider spread. Patents concerning both classes are mostly grouped along the diagonal, speaking to the idea that while these patents are spread more widely than just the AI pipeline, they still capture only a limited set of the technological contexts present in the dataset.

3.3.4 Classifier architectures

Conceptually, the two classes *AI for Sustainability* and *Sustainability of AI* are neither mutually exclusive nor collectively exhaustive. While some patents use AI to contribute both to the sustainability of AI itself as well as to the sustainability of other processes, others belong to neither class. Given this problem structure, I constructed a multilabel classifier. This architecture provides an individual label for each possible class, thus allowing for patents to belong to either one, both or neither category.

I trained a range of classifier architectures before selecting the best performing model to predict labels for all patents in the dataset. I used a 80/20 train-test split on the 1000 labelled patents, resulting in 800 observations available for training. Given this limited training data set, I applied k-fold cross-validation where I randomly split the data into k=5 subsamples. In each fold, I trained the model on 4 samples and validated on the remaining one which was alternated in each run. Thus, the choice of validation holdout did not influence the model performance, making K-fold cross-validation a robust approach, particularly suited for sparse labelled data (James et al., 2017).

While the labelled data are imbalanced, no upsampling or reweighting was used. In multi-label problems, these strategies tend to result in oversampling of common labels and thus introduce bias (Huang et al., 2021). However, to prevent different class distributions across train and test splits as well as across validation folds, which may impact classifier performance, stratified sampling was used. This method divides the dataset into strata according to the class assignment and then selects data points from each strata such that the class distribution is equal for each sample (i.e., test and train sample as well as each fold in the cross validation) (Neyman, 1992). To identify the best performing model, all architectures were trained and validated on the training dataset while the best performing model was also tested on the test set.

3.3.4.1 Model architectures

A range of different classifier architectures were computed. Firstly, I trained classifiers based on four different transformer models. These models were chosen due to promising results reported in recent patent classification studies (Craswell et al., 2020). Transformers are based on a neural network architecture which uses self-attention mechanisms to process input data in parallel. This allows the models to capture words' contextual meanings including long-term dependencies across text-sequences (Vaswani et al., 2017).

BERT: As a baseline, I used a BERT (Bidirectional Encoder Representations from Transformers) model (Devlin et al., 2019). This model was chosen since it is one of the most influential transformer models and has achieved state-of-the-art results across a range of NLP tasks (Koroteev, 2021). It represents text using both left and right context and was pretrained on masked language modelling and next-sentence prediction using data from the BooksCorpus and English Wikipedia (Devlin et al., 2019).

SciBERT: Secondly, I applied a SciBERT model (Beltagy, Lo, and Cohan, 2019). Based on the BERT architecture, SciBERT was trained on a corpus of 1.14 million full scientific papers. This domain-specific training may allow the model to understand the terminology and structure of scientific and technical documents, e.g., patents, more effectively than general-purpose models such as Bert. Especially since 18% of the sample comprises research from computer science, SciBERT is a promising model basis for classifying AI patents.

PatentSBERTa: Thirdly, I used PatentSBERTa (Bekamiri, Hain, and Jurowetzki, 2021). Based on Sentence-BERT (SBERT) and RoBERTa, the model is fine-tuned with supervised in-domain data from US patent claims. Potentially even more than SciBERT, this approach allows the model to capture the particularities unique to patents, including the technical jargon used in the texts. Initially proposed for classifying patents into CPC codes, this model is particularly fit for the purpose at hand due to the large database of patents on which it is trained.

For this study, all above models were finetuned to my specific classification task using an AutomodelForSequenceClassification structure.[5] As input data, I used the patent title, abstract and the first 300 words of the description if available. Patent titles tend to be very short and generic, so also considering the abstract and description can add valuable information. Since patent descriptions usually start with a description of the background and problem which a patent is aiming to solve (see also Figure 2.2 in Section 2.4), the initial 300 words are likely highly informative of the patent domain. On average, the input data consists of 423 words, which are well captured by the 512 input tokens of BERT based models (Devlin et al., 2019). Even among patents which have a description, the average length is 511 words and thus below the maximum token length.

In the hyperparameter tuning, different batch sizes as well as dropout rates and layers were tested in a grid search. As an optimizer, I used AdamW with a learning rate of 5^{-5}. All other hyperparameters were set to default. As is common for multilabel problems, a binary cross entropy loss function with logits loss (BCEWithLogitsLoss) was used, which applies a sigmoid layer to the classifier resulting in binary classification predictions. Compared to a separate sigmoid function followed by a plain binary cross entropy (BCE) loss function, BCEWithLogitsLoss has been shown to provide higher numerical stability (Qiu et al., 2023).

[5] https://huggingface.co/transformers/v3.0.2/model_doc/auto.html, accessed 15.07.2024.

Longformer: While the models discussed above have shown promising results on different classification tasks, several scholars contend that BERT-based models are not well suited for patent analysis as they cannot capture the full length of patent documents (Jiang and Goetz, 2024). To be able to take more text data into account in the classification algorithm, I therefore also applied a Longformer model (Beltagy, Peters, and Cohan, 2020). By leveraging a local windowed attention combined with task motivated global attention which is able to scale linearly with sequence length, this model can process documents of up to 4096 tokens, a significant advancement compared to the 512 maximum token length of BERT models. Longformer is pertained on masked language modelling and shows state of the art results across a number of tasks. In the study, I applied an open sourced LongformerForMultiLabelSequenceClassification algorithm.[6]

For the Longformer model, I used the patent title, abstract, claims and the first 3000 words of the description if available. Across all patents, this leads to an average document length of 3154 words. When only counting patents exhibiting both a description and claims, the average length is 4022 words, i.e., still below the maximum token length of Longformer models. To mitigate memory constraints, the batchsize was set to 4 and gradient accumulation with 4 accumulation steps was applied. This technique accumulates gradients for several batches instead of updating the model weights after every batch, thereby effectively imitating a larger batchsize (here 16) while keeping peak memory usage low (Sun, 2019). Again, the AdamW optimizer and BCEWithLogitsLoss were used while all other hyperparameters are set to default.

3.3.4.2 Loss functions

Secondly, I trained these four model architectures with different loss functions. In their baseline version, models were trained with BCEWithLogitsLoss. However, research indicates that due to the imbalanced class distribution, balancing loss functions may improve performance. The main idea is to re-weight the BCE loss function to give more attention to rare instance-label pairs. In their comparative study of different functions in the context of text classification, Huang et al. (2021) find that distribution balanced loss (DB) and class balanced focal loss with negative tolerant regularisation (CB-NTR) show the best performance across a range of datasets. Following this recommendation, I compared these two loss functions along with the traditional binary cross entropy loss function.[7]

3.3.4.3 Multimodal input data

Thirdly, I trained the four model architectures with different input data. The baseline models were trained only using textual data from the patent title, abstract and description (and claims for Longformer). As discussed, the combination of text

[6] https://github.com/jlealtru/website_tutorials/blob/main/notebooks/Multi_label_classification_longformer_tutorial.ipynb, accessed 15.07.2024.

[7] The code was used as provided by the paper https://github.com/Roche/BalancedLossNLP, accessed 15.07.2024.

components is necessary to capture detailed information about a patent. However, I also trained the classifiers on a combination of textual data and CPC codes. While, as discussed, the codes by themselves may obscure important innovation patterns, they do hold relevant information about patent type and domain. When combined with textual data, they may boost performance for the classification task. For this, I concatenated the document embeddings with a binarised matrix of the CPC codes before passing this information into the drop-out, batch normalisation and fully connected layers.

3.3.5 Model evaluation

For evaluation, I used the macro F1 score. This multilabel extension to the traditional F1 score, i.e., the harmonic mean of precision and recall, takes the unweighted average of F1 scores across classes. Since the dataset is imbalanced but all classes are equally important to the analysis, this metric is highly suited for the analysis (Banerjee et al., 2019). For all models, average performance across the validation folds is reported. In addition, I report the performance of the best model on the test data.

3.3.5.1 Overview of classifier architectures

Figure 3.8 presents an overview over all tested classifier architectures. Excluding hyperparameter tuning, the variations described above result in 24 overarching classifiers (4 models x 3 loss functions x 2 input data types). All models were trained with 5-fold cross validation on 5 epochs to prevent overfitting. Each of the Bert-based models was trained on two batch-sizes (16 and 32) and four drop-out layer constellations. For the Longformer models, computational costs were much higher such that no hyperparameter tuning was conducted. Including hyperparameter tuning, 222 models were trained.

To obtain final predictions on unlabelled data, the best performing model was again trained on all available labelled instances and then used to predict classes of unlabelled data.

3.4 Content analysis

After identifying the best-performing classifier, and predicting labels for all instances in the dataset, I used topic modelling to analyse patent contents. Traditionally, topic modelling methods such as Latent Dirichlet Allocation were based on bag-of-words representations of documents which disregard any semantic relationships between words. However, with the emergence of advanced embedding models such as BERT, new approaches have been proposed, including BERTopic (Grootendorst, 2022). This model produces state-of-the-art results in topic extraction tasks, making it an ideal choice for this thesis. BERTopic takes document embeddings as inputs, reduces their dimensionality, and then uses HDBSCAN to cluster them based on their proximity in the vector space. This results in clusters of semantically similar documents, i.e., "topics". To generate embeddings, the sentence-transformer implementation of

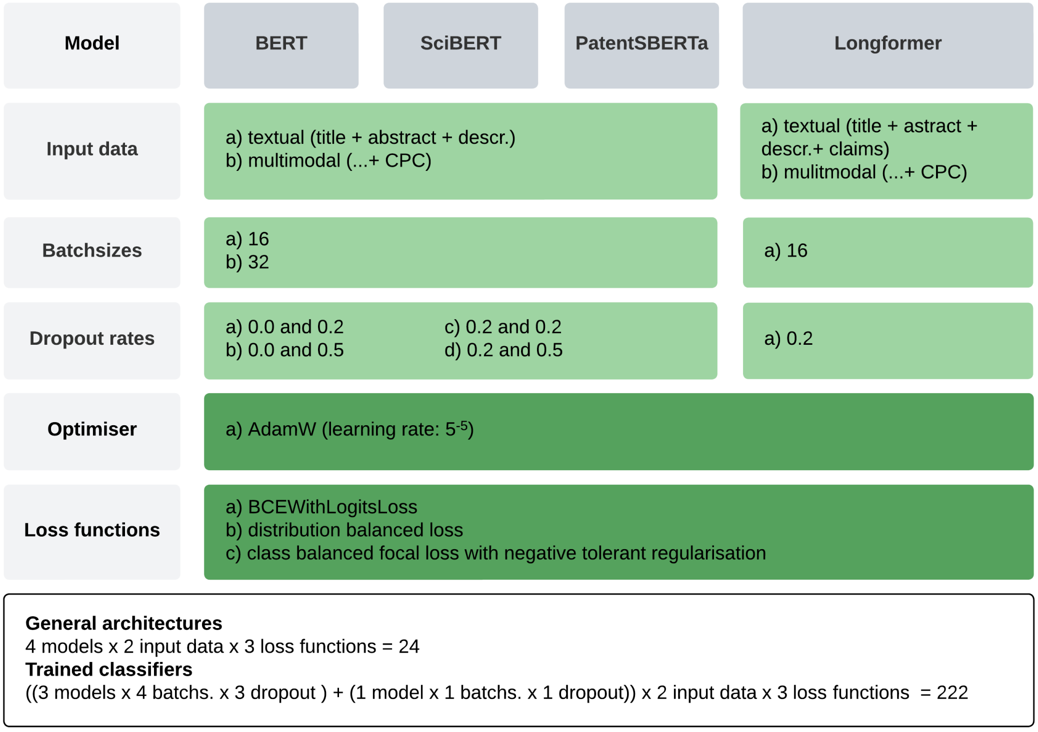


Figure 3.8: Overview of classifier architectures

Specter (Cohan et al., 2020) was used.[8] Built on SciBERT, this model is specifically trained on citation data to model inter-document relationships. This tends to result in more compact topic clusters in the embedding space, motivating my choice. Since Specter is a transformer-based model, no pre-processing (e.g., stopword removal) is required.

3.4.1 *AI for Sustainability*

To analyse *AI for Sustainability* patents by sector, I first identified topics with BERTopic. Then, a Llama 3 model was used to provide concise topic labels and descriptions. Launched by Meta in 2023, the open-source Llama model series (Touvron et al., 2023) is a family of auto-regressive LLMs using the Transformer architecture. The Llama 3 models, released on April 18, 2024, achieve state-of-the-art performance across a variety of NLP tasks, outperforming many closed-source LLMs including GPT-3. In this study, the 8 billion parameter version of the instructor model is used (aptha/Meta-Llama-3-8B-Instruct-Q4_0-GGUF).[9] Due to the large size, the model was quantized to 4-bit using the transformers bitsandbytes implementation.[10] Topics were then reviewed and manually clustered into technology groups and sectors.

[8] https://huggingface.co/sentence-transformers/allenai-specter, accessed 15.07.2024.
[9] https://huggingface.co/aptha/Meta-Llama-3-8B-Instruct-Q4_0-GGUF, accessed 15.07.2024.
[10] https://huggingface.co/docs/transformers/main/en/quantization/bitsandbytes, accessed 15.07.2024.

3.4.2 *Sustainability of AI*

To analyse *Sustainability of AI* innovation along the AI pipeline, BERTopic was used in a zero-shot setting. This technique allows users to find predefined topics in a dataset making it perfectly suited for cases such as here, where a specific conceptualisation of topical clusters is of interest (i.e., innovation along the AI pipeline as conceptualised by Wu et al. (2022)). In practice, the model embeds pre-defined topic descriptions and compares document embeddings using cosine similarity. The zero-shot topic descriptions used here are listed in Appendix B. To validate the topic model, 20 patents out of each cluster were manually reviewed. This process showed that the clusters produced by the model contained highly relevant patents, speaking for the validity of the approach.

3.4.3 Environmental impact

In the next step, I analysed the environmental impacts targeted in *Sustainability of AI* patents. Since patents concentrate on presenting the detailed workings of an invention, the environmental impact improvements promised by a technology are often mentioned only briefly. Accordingly, applying a topic model to this task resulted in no meaningful clustering of the patents. Instead, a keyword search was used. While rather simplistic, this methodology is a straight-forward and widely used approach to identify whether a specific issue is discussed in a document, even if mentioned only briefly. The four main environmental impacts of AI suggested by the literature relate to energy consumption, water consumption, waste and resource depletion, particularly rare metals which are crucial for many hardware components (Ligozat et al., 2022). For each impact category, a list of keywords was curated to capture relevant patents (see Appendix C). Patents can fall under several categories and those which do not fall under any category were counted as "other". Importantly, for this analysis only those patents were considered for which a description was available. This is because the patent title and abstract tend to only focus on the technical functioning of an invention. The description also includes details on the problem an invention aims to solve, making it likely that information about the environmental impact focus of a patent is contained there. Note, however, that this reduces the number of patents in the analysis, as not all for all patents in the dataset a description was available.

3.5 Actor identification

To analyse which actors most commonly patent sustainable AI technologies, I finally investigated assignees based the number of patents they hold. Patent assignees are the legal owners of a patent, i.e., the actor who has exclusive ownership over the patented technology (Azzam, 2009). Additionally, I analysed the geographic distribution of actors by calculating patent numbers by the country of residence of the assignee.

4 | Results

In the following, I will present my results. First, I review the performance of different classifier architectures designed to distinguish between innovation in *AI for Sustainability* and *Sustainability of AI* and identify the best performing model. This provides the basis for the subsequent content analysis, where I will investigate each subquestion to unveil whether patents, analysed using NLP methods, constitute a relevant element of inquiry to improve our understanding of innovation within of sustainable AI.

4.1 Classification results

Table 4.1 summarises the performance of all 24 classifier architectures.

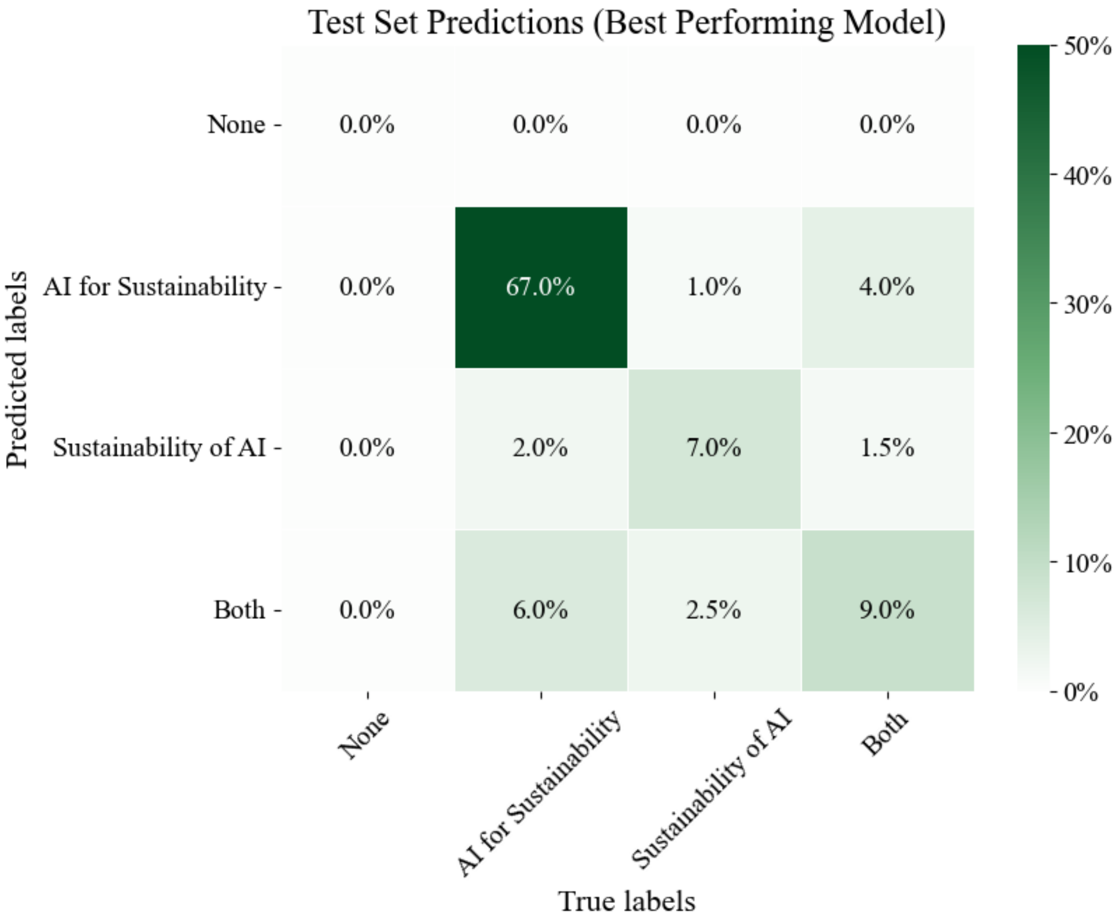
Model	Input Data	Loss Function	Macro F1 (Val avg)	Accuracy (Val avg)
BERT	**TAD**	BCE	0.861	0.844
		DB	0.840	0.835
		CB-NTR	0.841	0.859
	TAD + CPC	BCE	0.834	**0.862**
		DB	0.845	0.850
		CB-NTR	0.841	0.861
SciBERT	**TAD**	BCE	0.871	0.860
		DB	0.856	0.845
		CB-NTR	0.849	0.870
	TAD + CPC	BCE	0.844	0.863
		DB	0.841	0.862
		CB-NTR	0.858	**0.881**
PatentSBERTa	**TAD**	BCE	0.874	0.851
		DB	0.866	0.841
		CB-NTR	0.836	**0.871**
	TAD + CPC	BCE	0.831	0.825
		DB	0.828	0.849
		CB-NTR	0.848	0.862
Longformer	**TADC**	BCE	0.786	0.460
		DB	0.786	0.460
		CB-NTR	0.823	0.**857**
	TADC + CPC	BCE	0.754	0.731
		DB	0.795	0.704
		CB-NTR	0.809	0.832

Abbreviations: TADC - title, abstract, description, claims; CPC - CPC codes; BCE - binary cross entropy loss; DB - distributed loss; CB-NTR - class balanced focal loss with negative tolerant regularisation
Three decimal places are shown to expose marginal differences. Best result per transformer model in bold, overall best result in green.

Table 4.1: Classifier performance

The best performing model uses SciBERT and multimodal input data with a CB-NTR loss function. In the cross validation, this model reaches an average macro-F1 score of 88.1% and an average accuracy of 85.8%. On the test set, the model reaches a macro-F1 score of 86.4% and an accuracy of 84.5%. The slight difference in scores is likely due to statistical fluctuations: Across the five folds of the cross-validation, the macro-F1 score ranges between 86.6% and 91.6%, indicating that the test set performance may also fall within 2-4 percentage points around the average.

Figure 4.1 displays the confusion matrix of true and predicted labels in the test set. The model performs well in identifying *AI for Sustainability* patents with a sensitivity (true positive rate) of 89.3%. With 66.7%, the sensitivity for *Sustainability of AI* patents is slightly lower. However, in both cases, most misclassified patents were predicted to belong to both classes. Thus the model at least partially recognised the correct class. Patents that actually belong to both classes were identified with a sensitivity of 62.1%. Here, all incorrect predictions were classified to concern only one instead of both branches, thus still partially recognising the correct class. The test set contains no patents that belong to neither class.



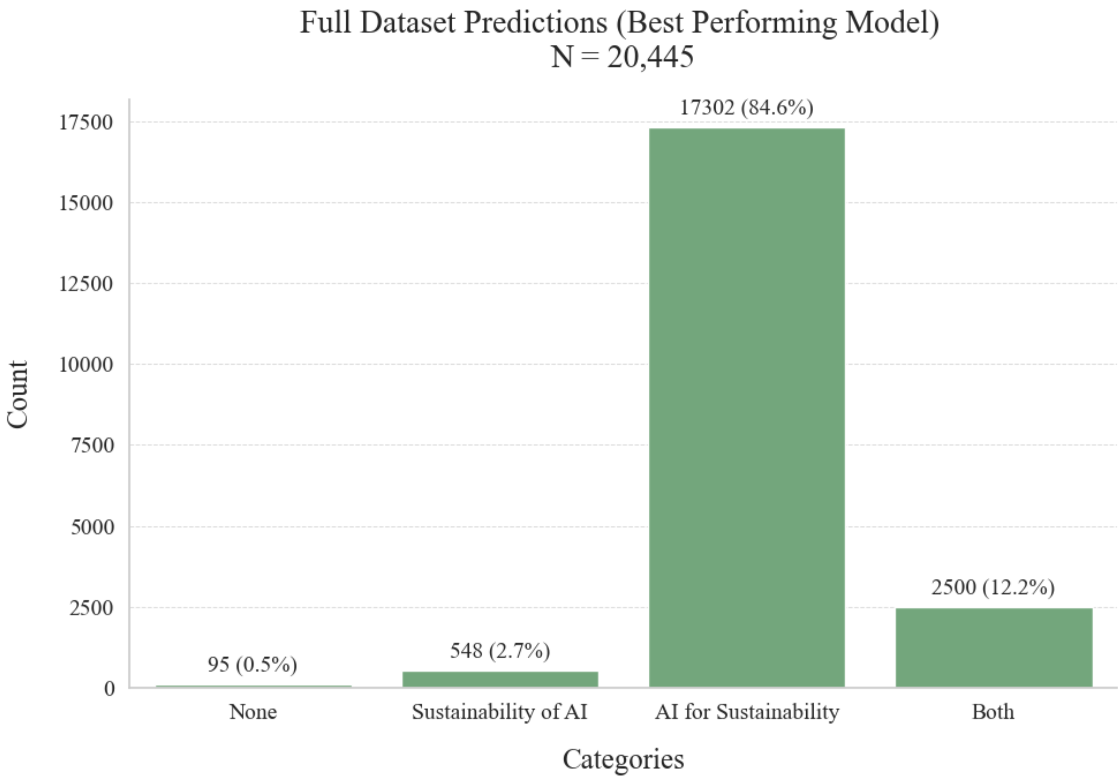
Confusion matrix of true and predicted labels of the best performing model (SciBERT with multimodal input data and a CB-NTR loss function) on the test set.

Figure 4.1: Confusion matrix of true and predicted labels on the test set for best performing model

To most effectively predict labels for unseen patents in the dataset and analyse the subquestions, the best performing model was trained once more using all 1000 labelled instances.

4.2 SQ 1: Balance in innovation activity

In the content analysis, I first assess how innovation activity is balanced between the fields of *Sustainability of AI* and *AI for Sustainability*. Applied to the full dataset of 20,445 patents, the classifier predicts 17,302 patents (84.6%) to belong to the category "AI for Sustainability" and 548 patents (2.7%) to belong to "Sustainability of AI". 95 (0.5%) are predicted to belong to neither and 2,500 patents (12.2%) are predicted to belong to both classes (see Figure 4.2). This means that more than 97% of inventions relate to *AI for Sustainability*, while less than 15% relate to the *Sustainability of AI*. This extreme imbalance in innovation activity is noteworthy and indicates that, in line with the wider discourse, applying AI is much more popular than working on reducing its environmental impact.

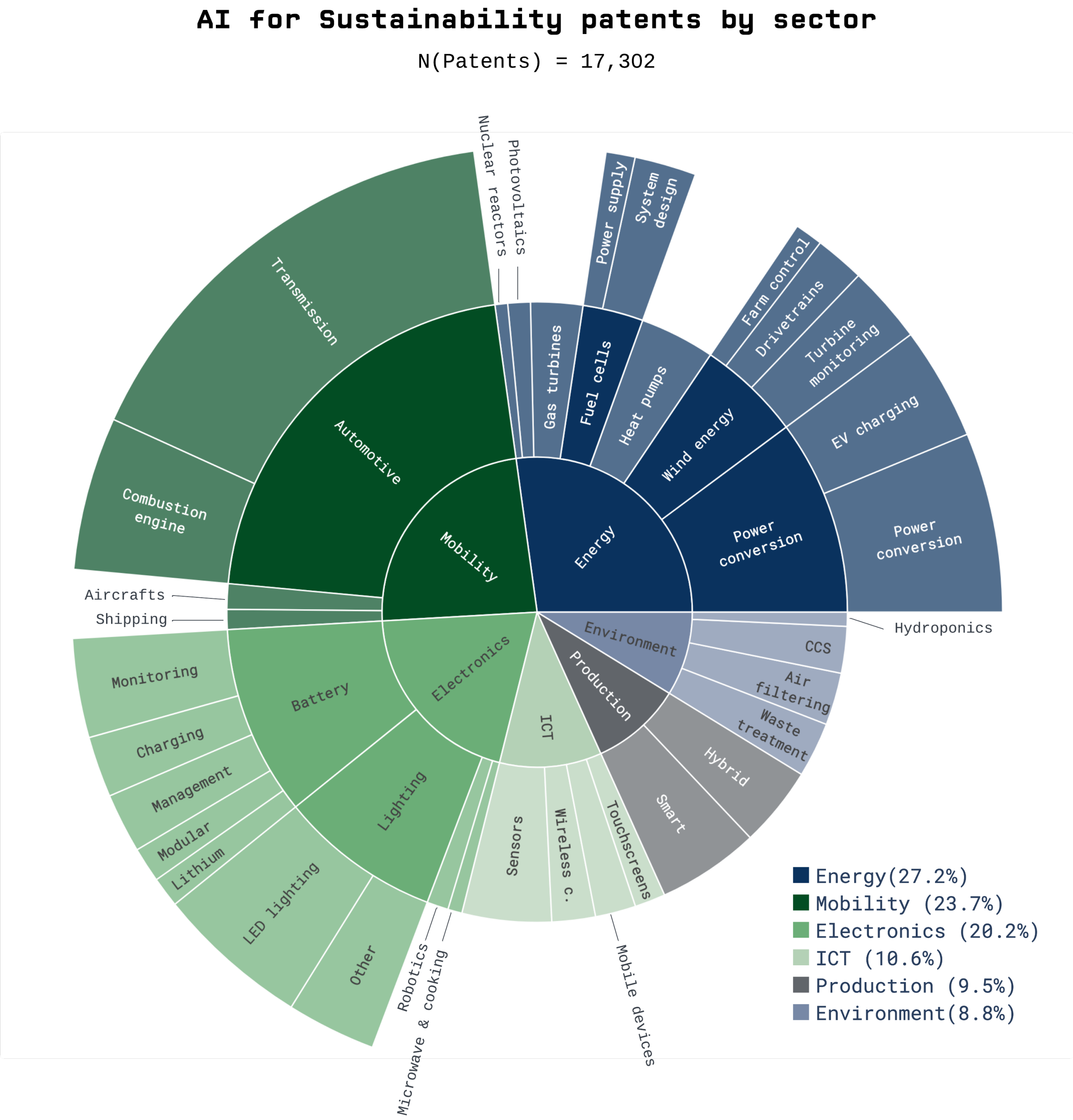


Predicted labels of the best performing model (SciBERT with multimodal input data and a CB-NTR loss function) on the full dataset.

Figure 4.2: Predicted labels for full dataset

4.3 SQ 2: *AI for Sustainability* innovation

Next, I analyse how *AI for Sustainability* innovation is clustered across different sectors and technologies. For this, I consider all patents classified as concerning



Sunburst chart of *AI for Sustainability* clusters organised by sector. Clusters were obtained using a BERTopic model and were manually organised into sector groups.

Figure 4.3: AI for Sustainability innovation by sector and technology

either only *AI for Sustainability* or both classes. Figure 4.3 displays a sunburst chart visualising the clusters identified with the topic model. The clusters were manually organised into a hierarchical structure, where the inner circle of the sunburst chart represents sectors, the middle circle shows technology groups and the outer circle includes specific technologies.

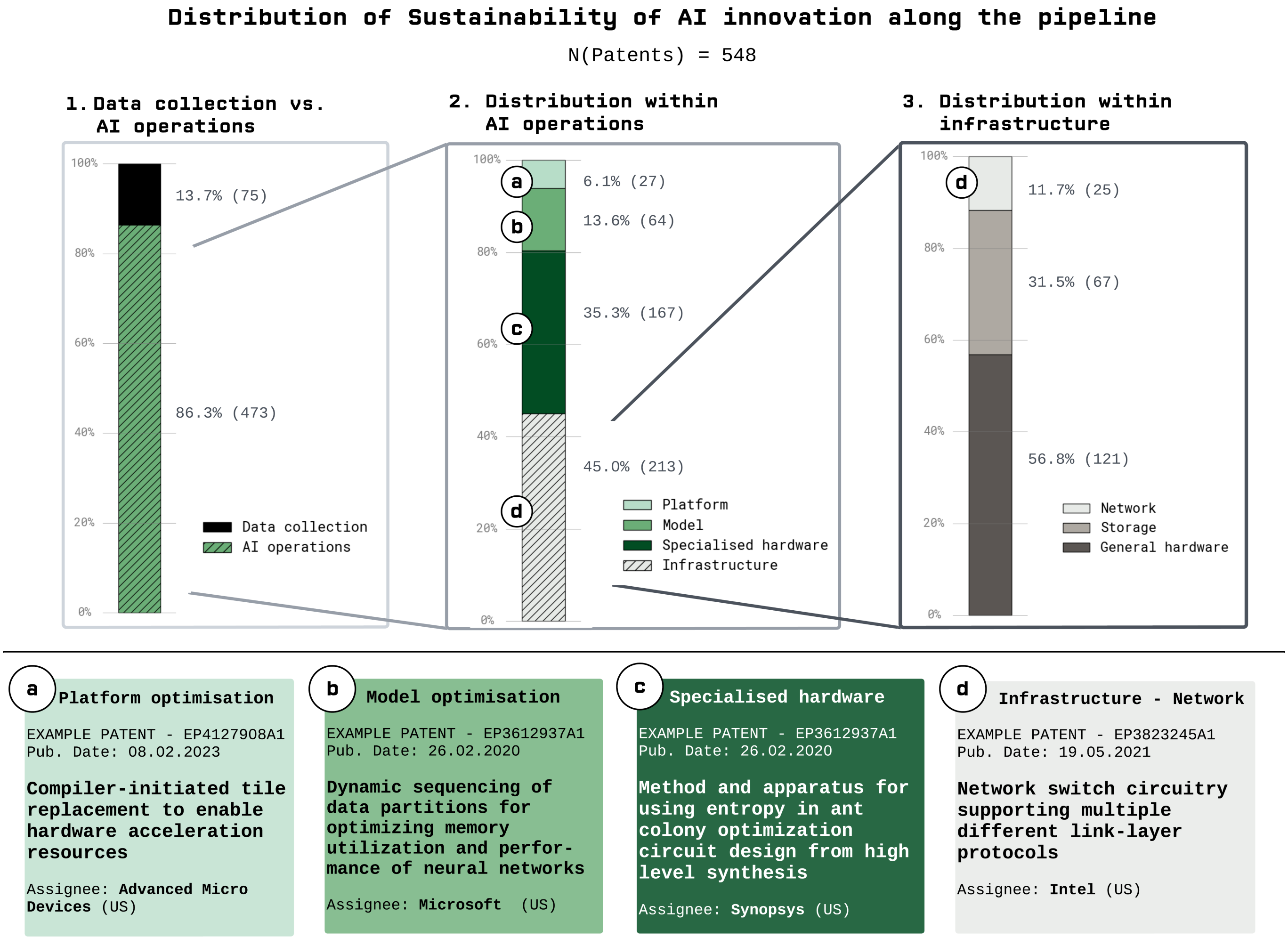
Overall, it is notable how widely the applications are spread, spanning six different sectors: energy, mobility, electronics, information and communication technology (ICT), production/manufacturing and environment. Most commonly, AI is applied in the context of sustainability in the energy sector (30.1% of patents). Within this sector, AI is applied to power conversion on the one hand. This group captures technologies for power transfer, voltage regulation, and Electric Vehicle (EV) charging. On the other hand, AI is used for different types of energy production, including wind, solar, thermal, gas and nuclear energy, as well as fuel cells. This speaks to the idea that diverse opportunities arise for sustainable AI applications in the energy sector, potentially motivating closer attention from policy and funding.

The second largest sector is mobility (20.9% of patents). This sector uses AI mostly to make automotive technologies more sustainable, for instance through vehicle transmission systems, such as designs for gear pairs, clutches and selective engagement mechanisms to improve vehicle efficiency. Within electronics, the third-largest sector (20.2%), AI applications focus mainly on batteries including battery design, charging and monitoring, and on lighting. Fourthly, AI is used to improve environmental sustainability in ICT (12.5% of patents). Here, AI is mostly used in sensor technologies, wireless communication systems, mobile devices and touchscreen design. Within production and manufacturing (8.7%), the fifth largest sector, sustainable AI innovation has two main pillars: smart production systems, where data analysis is used to optimise manufacturing processes, as well as hybrid production methods, where 3D printing and subtractive processes (e.g., grinding or drilling) are combined in the same machines to improve efficiency in the fabrication of products. Finally, AI is also applied to specifically environment-related technologies (7.6%). For instance, it finds application in waste treatment, air filtering, carbon capture and removal as well as agriculture (e.g., hydroponics).

4.4 SQ 3: *Sustainability of AI* innovation

Next, I analyse how *Sustainability of AI* innovation is clustered along the AI pipeline. I start with an analysis of those patents which only concern *Sustainability of AI* but not both classes. This is because many more patents relate to both rather than just the one class such that a wider view may obscure more fine-grained patterns.

Generally, with only 548 patents focusing exclusively on the *Sustainability of AI*, the entire pipeline attracts very little patenting activity. Figure 4.4 displays how innovation is clustered across the AI pipeline. This shows in even more detail, how patenting numbers in the field are extremely low. In the high-level overview, innovation shows a strong focus on AI operations (473 or 86.3% of patents) over data collection technologies such as sensors and tracking devices (75 or 13.7%).



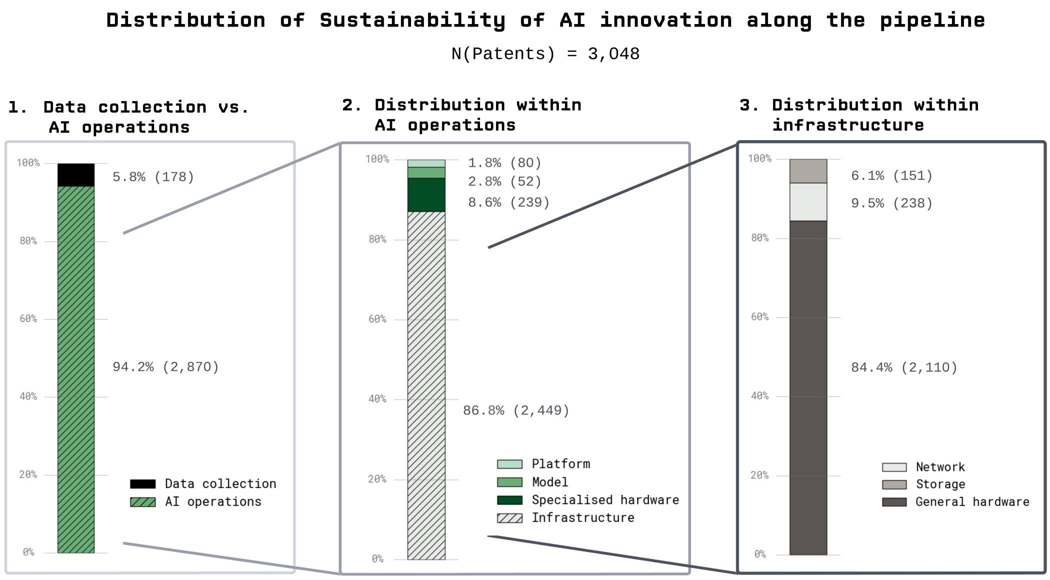
Innovation clusters obtained using a zero-shot BERTopic model. Clusters were aligned along the AI pipeline, with zoom-ins to detail distributions. a) to d) present example patents for each AI operation.

Figure 4.4: Overview of Sustainability of AI innovation clusters along the AI pipeline (Sustainability of AI only)

Within AI operations, the smallest cluster relates to AI platform technology, comprising 6.1% or 27 patents. Platforms are frameworks providing the necessary software infrastructure and interfaces for using AI models and can span across the entire workflow, from data preparation to model design and training. An example patent of this cluster (publication number: EP4127908A1) proposes a processing system that uses a compiler to automatically identify and replace source code with high-performance tensor operations executable by a specialised hardware accelerator (e.g., a GPU). Thus, it integrates the optimisation of code execution on a platform-level, facilitating sustainable computing for users.

The next largest cluster comprises specific AI model architectures. This cluster includes 13.6% of operations patents, with a total of 64 patents. For instance, one patent (publication number: EP3612937A1) proposes a neural network architecture with dynamic sequencing of data partitions. This prioritizes fully processing one layer of the network before moving on to the next layer while being able to adapt dynamically based on memory availability, thus improving memory utilisation and performance. Thirdly, 167 operations patents (35.3%) relate to specialised AI hardware. For instance, one patent (publication number: EP3612937A1) proposes a technology that uses entropy as an efficient hardware implementation method for ant colony optimization for designing circuits.

The largest group of operations patents (45.0% or 213 patents) relate to general AI infrastructure. Within AI infrastructure, technologies can be further clustered in network connectivity (11.7%), storage (31.5%) and general hardware (56.8%), with the latter including for instance power supply and conversion as well as cooling systems needed for efficient and reliable computing. An example patent (publication number: EP3823245A1) relating to network technology proposes a switch circuitry, a hardware component which manages the data traffic between different devices in a network.



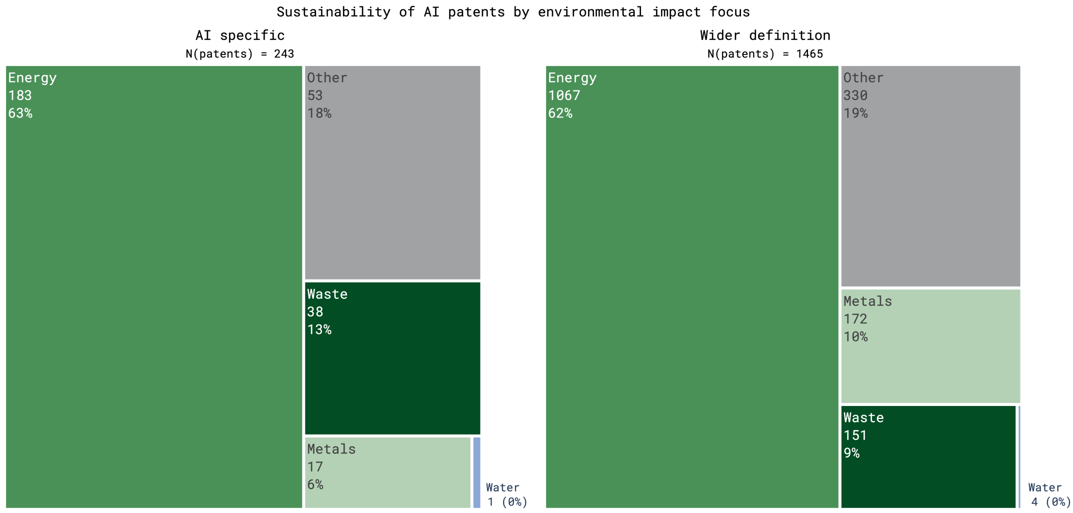
Innovation clusters obtained using a zero-shot BERTopic model. Clusters were aligned along the AI pipeline, with zoom-ins to detail distributions.

Figure 4.5: Overview of Sustainability of AI innovation clusters along the AI pipeline (wider definition)

When considering the wider definition of Sustainability of AI patents, i.e., also those patents which at the same time relate to AI for Sustainability, the proportions change drastically with the vast majority of patents relating to general hardware infrastructure (see Figure 4.5). This is intuitive: technologies in the overlap concern for instance electronic components which can be used across a variety of contexts including but not limited to AI.

4.5 SQ 4: Environmental focus of *Sustainability of AI* inventions

In the next step, I analyse which environmental impact dimensions are the focus of *Sustainability of AI* inventions. Figure 4.6 displays the distribution of patents by environmental focus. As discussed earlier, this analysis includes only those patents where a patent description was available, explaining the lower overall patent counts.



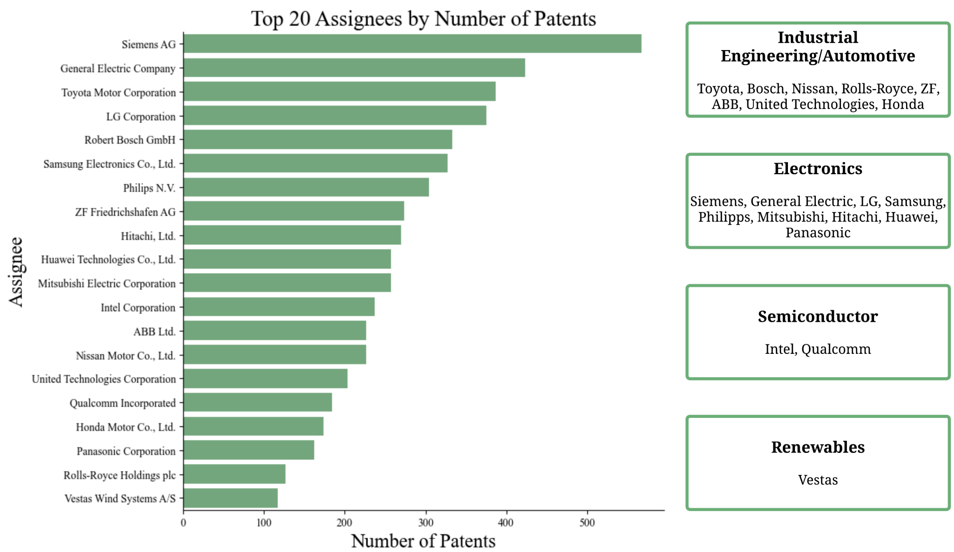
Treemap plot of *Sustainability of AI* patents by environmental impact focus. Patents are included if words related to a type of environmental impact are mentioned in abstract or conclusion. Patents can be included in several categories and publications without description are excluded. On the left, patents only falling into the *Sustainability of AI* class are presented. On the right, patents falling into both categories are included.

Figure 4.6: Sustainability of AI patents by environmental impact focus

Both when considering only *Sustainability of AI* specific patents as well as when including patents falling under both classes, the vast majority of inventions focus on reducing energy consumption (63% and 62%). Within the former group, waste is the second largest environmental impact focus, with 13% of patents relating to reducing waste or toxicity, for instance by improving product lifespan. Only 6% of patents focus on reducing the consumption of rare metals and only one patent discusses the reduction of water consumption. Within the wider *Sustainability of AI* definition, the focus on rare metals is more prevalent than waste, pointing to the idea that many of the general AI infrastructure inventions improve on the usage of rare metals. Again, water is by far the smallest focus area, with 4 patents focusing on this impact factor.

4.6 SQ 5: Major actors in sustainable AI patenting

Finally, I investigate the major actors patenting solutions in sustainable AI. Figure 4.7 shows the top 20 patent assignees in sustainable AI.



On the left, top assignees by number of patents are displayed. On the right, assignees are clustered by sector focus.

Figure 4.7: Top 20 patent assignees in sustainable AI

The market is highly fragmented. The top assignee Siemens holds less than 3% of patents in the field. Interestingly, the top assignees do not include typical AI companies. Instead, most of the companies operate in industrial engineering (mostly automotive) or electronics. Two players produce semi-conductors and one firm is in renewable energy. Analysing assignees by country reveals that the largest share of European sustainable AI patents, i.e., 4,000 patents or 19.6%, are held by US American firms (see Figure 4.8). With ca. 3,000 patents each, Germany and Japan are the second and third largest sustainable AI patent holders. Interestingly, when looking at the top five countries, only one European country is included, while three Asian countries are (Japan, China, Korea).

4.7 Patents as a framework of sustainable AI innovation

These analyses illustrate how patents, when analysed using NLP, can illuminate large-scale innovation patterns, specific inventions and important actors. These relevant insights indicate that patents do indeed provide a relevant element of inquiry to improve our understanding of innovation within the field of sustainable AI.

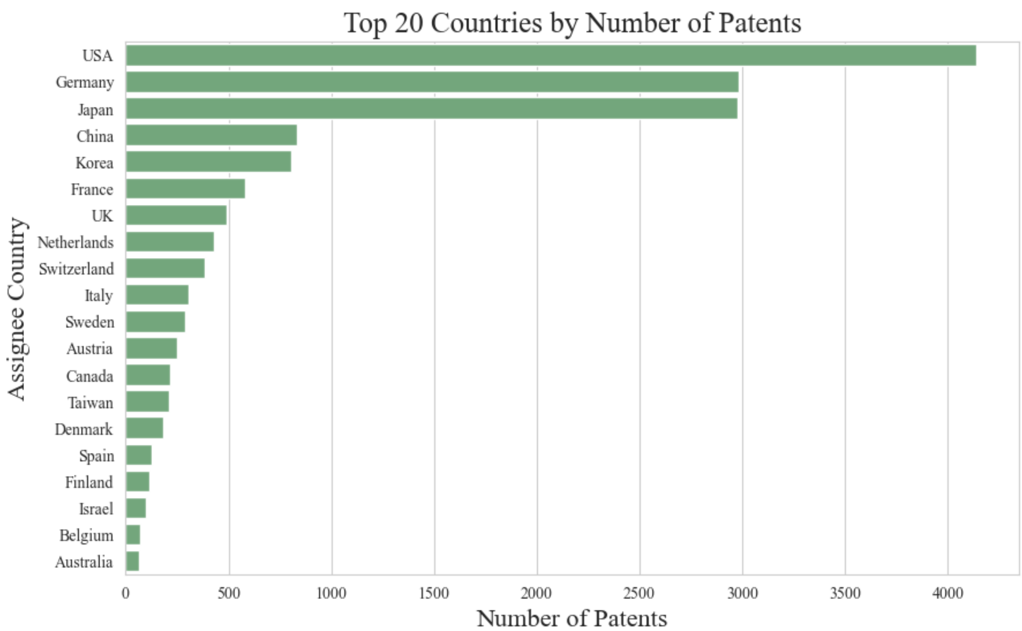


Figure 4.8: Sustainability of AI patents by country

5 | Discussion

5.1 Principal findings

This thesis has investigated patents as a data source and framework for innovation analysis in sustainable AI. I find that NLP-based patent analysis can contribute immensely to a profound understanding of innovation in this area by illuminating patterns in innovation activity, content, and actors. Using a text-based classifier, I reveal that innovation activity in *AI for Sustainability* hugely outweighs *Sustainability of AI*. Within the former, research is largely focused on the energy, mobility and electronics sectors. Within the latter, innovation shows a strong focus on specialised AI hardware and AI infrastructure. Notably, *Sustainability of AI* patents mostly tackle the energy consumption of AI systems, while other environmental impacts such as water consumption remain highly understudied. Finally, I find that the sustainable AI patent landscape is highly fragmented, with most assignees being based in the US, Germany and Japan. Interestingly, the most prominent AI players do not emerge as major actors within sustainability. These results powerfully illustrate that patents constitute a highly relevant element of inquiry which substantially improves our understanding of innovation in sustainable AI.

5.2 Patent classifier

Before interpreting my results, I will briefly discuss the sustainable AI classifier which provides the methodological foundation of this study. As anticipated, both using an alternative loss function as well as including multimodal input data improved the classifier performance. However, the superior performance of the SciBERT model architecture is noteworthy. Despite PatentSBERTa's finetuning on patent data and the Longformer model's capability to process more text, SciBERT, which was finetuned on general scientific literature, emerged as the best model. A possible explanation is that SciBERT was extensively trained on computer science literature. Since the sustainable AI patents considered here closely relate to this field, the model may be particularly fit for the task. Another reason may be that PatentSBERTa is trained on US instead of European patents which may differ systematically, explaining the lower performance.

The top-performing model excels in correctly identifying *AI for Sustainability* patents, but performs slightly less well for *Sustainability of AI* patents or patents classified under both classes. This may be due to the imbalanced label distribution, where the classifier was exposed to a significantly larger number of *AI for Sustainability* patents compared to the other two categories. Nonetheless, the overall performance is very high, especially compared to other AI-related patent classification studies. There, common F1 score levels range between 0.4 and 0.6 (Giczy, Pairolero, and Toole, 2022; S. Li et al., 2018) which is much lower than the 0.88 achieved by my best-performing model. This allows for high confidence in the classifier as the foundation of this study.

5.3 Contextualisation in the wider literature

I now interpret my findings which provide pioneering insights into innovation patterns in sustainable AI.

5.3.1 SQ 1: Balance in innovation activity

The first main insight revealed in this study is that there is an extreme imbalance between innovation activity in the fields of *AI for sustainability* and *Sustainability of AI*. More than 97% of inventions pertain to the former while less than 15% address the latter.[1] This disparity is deeply worrying, given that both dimensions are valuable and necessary components of establishing sustainable AI. The limited attention on the *Sustainability of AI* is particularly alarming as the AI market and therefore its environmental impact continues to grow (Bashir et al., 2024; Grand View Research, 2024a). Limiting these damages should be a top priority.

To actually prioritise the *Sustainability of AI*, it is imperative first to acknowledge the harm incurred by AI systems. As discussed, large AI companies, industry and political experts, often portray AI as the (sole) solution to global challenges. However, this narrative obscures the immense environmental costs of these technologies, hindering the effective alignment of AI with sustainability. To counter these misleading perceptions of AI, educational efforts and realistic reporting are essential. Secondly, effective policies must be implemented to incentivise green AI innovation. For instance, this could be achieved by conditioning R%D funding for AI research on efforts such as the usage of renewable electricity or the development of energy efficient equipment (Cowls et al., 2021, p. 302).

5.3.2 SQ 2: *AI for Sustainability* innovation

Analysing *AI for Sustainability* patents individually showed that AI models are applied to a variety of sectors and technologies. Cowls et al. (2021) argue, that this should be considered a positive dynamic: climate change comes with a host of challenges and damages, many of which are extremely severe. This offers a wide array of options to use AI for good and harness it to its full potential. With the largest cluster of *AI for Sustainability* patents focusing on the energy sector, it also appears that innovators are working on one of the most powerful levers. Energy supply (electricity and heat production) causes almost 50% of all European CO2 emissions (International Energy Agency, 2021). Using AI to integrate renewable sources or to forecast supply and demand for optimal energy distribution (Serban and Lytras, 2020) is thus an important step towards more sustainable societies.

While innovation in *AI for Sustainability* therefore gives rise to hope, it is crucial to not that applying AI with the aim of furthering sustainability does not guarantee a positive outcome. Due to high computational costs, some AI applications may create more harm than they mitigate. To avoid this, it is imperative to establish

[1]Note that these numbers do not add up to 100% because 12% of inventions relate to both fields.

consistent measurement and reporting standards for the environmental impacts of algorithms (Cowls et al., 2021; Henderson et al., 2020; Lacoste et al., 2019; Ligozat et al., 2022). Patents could play an important role in this. If inventors were required to detail and quantify how a technology enhances sustainability while considering its environmental costs, this could expose potentially harmful projects and provide an incentive to develop better products.

5.3.3 SQ 3: *Sustainability of AI* innovation

Analysing patents along the AI pipeline revealed that innovation focuses on AI operations rather than data collection, with significant efforts on specialised AI hardware and infrastructure innovation. While, as discussed, it is obvious that all of these areas are highly understudied, it remains unclear whether the distribution of innovation efforts, too, needs steering. One study on AI operations at Meta suggests that iterative optimisations across different optimisation areas can result in substantial power emission reductions, indicating the a wide spread of innovation is favourable (Wu et al., 2022). However, more robust insights are needed detailing which optimisation areas may hold the most potential for reducing the environmental impacts of AI systems. For this, it is necessary to go beyond studying separate elements of the pipeline, e.g., specific model architectures and their carbon footprints (Chien et al., 2023; Naidu et al., 2021; Patterson et al., 2021; Verdecchia et al., 2022), and compare different elements in their capacity to improve sustainability. This will allow practitioners and policymakers to optimally choose which problems to work on and thereby accelerate the journey to more sustainable AI systems.

5.3.4 SQ 4: Environmental focus of *Sustainability of AI* inventions

When examining the environmental impacts targeted by *Sustainability of AI* innovation, it stands out that most patents focus on improving the energy consumption of AI systems. Crucially, making systems more energy efficient is a key lever to limiting the carbon emissions of the sector and combating the climate crisis (Shenoy, 2023). However, to ensure that efficiency gains actually translate into lower overall emissions, policy intervention is needed. This is because, paradoxically, improving the efficiency of AI could actually increase the overall AI carbon footprint. Known as Jevon's paradox, resource efficiency can function as a stimulus, incentivising the creation of additional novel AI use cases (Nishant, Kennedy, and Corbett, 2020; Widdicks et al., 2023). To avoid this trap, macroeconomic studies point to the importance of environmental policy interventions such as taxation or cap-and-trade systems (Freire-Gonzalez, 2021; Mashhadi Rajabi, 2022; Widdicks et al., 2023).

While a considerable number of patents focus on the energy consumption of AI systems, other environmental impacts remain neglected. This is highly problematic as AI systems come with a range of dangerous consequences (Wright et al., 2023). For instance, reducing the need for rare metal in the production of hardware components is discussed in only 10% of patents. However, mining such metals drives deforestation and has been shown to produce pollutants and hazardous materials which enter food and water supplies (Balaram, 2019; Nayar, 2021; Siqueira-Gay and Sanchez, 2020). Similarly, the (e-)waste produced by AI systems, which even less than 10% of patents mention, can lead to hazardous chemicals entering water supplies. This can have catastrophic affects on the health of local communities (Forti et al., 2020; Nayar, 2021). Finally, the water consumption driven by electricity generation and hardware cooling is a substantial factor in worldwide water scarcity (P. Li et al., 2023; Mytton, 2021), exacerbating droughts and even limiting local communities access to clean freshwater (Bast et al., 2022). The low number of patents working on alleviating these environmental consequences is alarming and reflects the minimal regulatory attention given to non-energy related impacts of AI (Coeckelbergh and Saetra, 2023; Kak and Myers West, 2023). This study thus underscores the urgent need for effective policy to stimulate diverse innovation that mitigates the myriad of environmental consequences caused by the AI sector.

5.3.5 SQ 5: Major actors in sustainable AI patenting

Finally, this thesis finds that the sustainable AI patenting landscape is highly fragmented. The top assignee Siemens holds only 3% of patents. On the one hand, this could be a positive sign indicating that a range of companies are interested in innovating in this area. However, the overview of top assignees also suggests that sustainability is not yet an important field for core AI players. IBM, Microsoft and Google held 34%, 24% and 19%, respectively, of all AI patents in 2018 (Habibollahi Najaf Abadi and Pecht, 2020). Combined, these three companies therefore owned 77% of all patented AI innovation. Yet, they do not hold anywhere near as large a share of sustainability patents and do not even appear in the top 20 assignees. Given how much intellectual prowess and resources are concentrated in these firms, it is alarming how little they contribute to the field of sustainable AI. Designing policy requiring powerful firms to focus more effort on this field could unlock substantial funds and progress, necessary for achieving genuinely sustainable AI.

I also find that patent assignees in sustainable AI are highly concentrated in high income countries, especially the USA, Germany, and Japan. On the one hand, this is highly problematic because it extends, and creates new, long term dependencies where especially lower and middle income countries can no longer catch up to the technological frontier, leaving them reliant on richer economies (Hartmann et al., 2021; D. Li et al., 2023). However, improvements in the sustainability of AI systems, even if proposed in Europe or the US, could also widen access to AI. By lowering the energy and resource consumption of models, AI can be used in contexts were fewer resources are available (Fan, Yan, and Wen, 2023). By facilitating the use of AI in healthcare or energy management, sustainability innovation could thus unlock enormous benefits.

5.3.6 Patents as a framework of sustainable AI innovation

Overall, my findings illustrate the immense potential of investigating sustainable AI through the lens of patents. By illuminating large-scale patterns in innovation activity, content, and actors, patent analysis can contribute substantially to our understanding of innovation in this field. The insights generated by this can in turn function as a crucial policy guidance, informing three key takeaways. Firstly, more research in *Sustainability of AI* must be incentivised, which focuses on a range of different environmental impacts. Secondly, better reporting of the sustainability contribution of *AI for Sustainability* inventions is required, where patents could provide a useful framework. Thirdly, influential and resourceful AI players must be incentivised to contribute more towards the sustainability of the sector. By addressing these areas, we can pave the way for an environmentally conscious AI landscape.

5.4 Limitations

This thesis is subject to several limitations, concerning, on the one hand, patents as a data source, and on the other hand, the conducted NLP analysis. As discussed, patents cannot account for the specific contexts within which a technology is produced, distributed and applied. "Sustainable" patents may therefore propose technologies that *could* reduce environmental impacts, but it is not certain that they are always used in the way intended, and how they are embedded in supply chains. For instance, more efficient GPUs contribute little to the sustainability of AI systems when they are severely under-utilised as is often the case (Wesolowski et al., 2021). Similarly, efficiency-enhancing technologies when applied to "dirty" sectors such as oil and gas can actually cause more harms than benefits (Coeckelbergh and Saetra, 2023).

Patents also capture only a subset of innovation. While I argue that this subset is of relevant size and content, it must be acknowledged that many inventions are not patented. Specific AI models, for instance, are often protected by trade-secrecy rather than patents in order to have more flexibility (La Diega, 2018). Especially academic researchers and smaller companies may forgo protection altogether and open-source their inventions (Calvin and Leung, 2020).

Regarding the NLP analysis, one shortcoming relates to the labelling. Due to limited resources, only 1000 patents were hand labelled and all labelling was performed by the author with no additional human validation. While clear inclusion and exclusion criteria were laid out and clustering validates the labelling results, this limitation may have resulted in some bias in the data. A second shortcoming is that the topic modelling comes with some simplifications. Not only does this approach often focus on large scale patterns while potentially obscuring more fine-grained dynamics. I also model topics as static over time, when especially AI as field is advancing quickly meaning that topics may change. Nonetheless, due to the careful manual validation as well as the presentation of specific example patents, I argue that the topic modelling performed here can still give reliable and accurate insights into sustainable AI innovation.

5.5 Avenues of future research

The findings of this study point to several avenues worthy of further attention. These can be clustered into four strands. Firstly, this thesis reveals the urgent need for more research aiming to make AI more sustainable. Secondly, additional evidence is required which illuminates which areas of the AI pipeline yield the most potential to improve the sustainability of AI systems and should thus be focused on. Thirdly, this analysis of European patents should be complemented with research focusing on other regions as well as open-source innovation, for instance analysing activity on GitHub. Finally, by showing how patents can illuminate innovation patterns, I hope to inspire further inquiry into this methodological approach. Future research could focus on other sectors and test other NLP models in their capacity to provide large-scale, policy-informing evidence.

6 | Conclusion

In recent years, the idea of harnessing AI to combat the climate crisis has garnered considerable attention. Pioneering initiatives are utilising AI to tackle diverse challenges, from flood prediction to ocean cleanup. However, it is often overlooked that the AI sector itself is a significant contributor to greenhouse gas emissions and environmental degradation. To establish AI that aligns with environmental sustainability, it is imperative to address these two facets concurrently: we must deploy AI to further sustainability (*AI for Sustainability*) and work on making AI itself more sustainable (*Sustainability of AI*). Crucially, the current techno-solutionist discourses around AI suggest that, without effective policy intervention, innovation efforts will not be optimally balanced between these two aspects. However, with the climate crisis exacerbating rapidly, we cannot afford to maintain unsustainable AI systems. Thus, to ensure that researchers and developers focus on the most pressing issues, it is crucial to survey innovation efforts, identifying both progress and existing gaps. To this aim, the present thesis investigates whether patents, analysed using NLP techniques, can provide a relevant element of inquiry for enriching our understanding of innovation in the field of sustainable AI.

Using a text-based classifier, I reveal that the *Sustainability of AI* is severely under-researched, particularly when thinking beyond energy consumption as the sole environmental cost of AI systems. Further, powerful AI players show alarmingly little interest in sustainable AI innovation, with efforts instead stemming from electronics and industrial engineering companies. However, there is also cause for hope: While being in the early stages, innovation activities in both *AI for Sustainability* and *Sustainability of AI* show a diverse range of approaches and ideas. With patenting in sustainable AI on a strong upward trajectory, these hopefully represent just the beginning of the progress necessary to align AI with environmental sustainability. Overall, these insights reveal that patents, analysed using NLP, constitute a highly relevant element of inquiry to improve our understanding of sustainable AI innovation.

My results have important implications. Firstly, they powerfully illustrate the urgent need for better policies, steering the AI sector toward sustainability. Specifically, three key recommendations emerge. Firstly, stronger incentives are needed for companies to engage in sustainable AI innovation, particularly inventions focusing on the *Sustainability of AI* which take into account the variety of environmental damages caused by AI. Secondly, we require better reporting of the sustainability contribution of *AI for Sustainability* inventions to avoid the promotion of technologies which cause more harm than benefits. Thirdly, especially major AI players must be incentivised to leverage their enormous resources to improve to the sustainability of the sector. As a second contribution, my findings illuminate the immense potential of using NLP-based patent analysis to investigate innovation activity. By providing a labelled dataset and a classifier to distinguish between inventions in *AI for Sustainability* and *Sustainability of AI*, I hope to facilitate future research in this critical field. At the same time, the methods applied here could be used to study other sectors and technology fields and generate large-scale, policy-informing evidence.

Finally, this thesis highlights one more takeaway. While companies like Google are painting optimistic pictures of AI as the solution to global challenges, the empirical evidence on the trajectory of sustainable AI innovation suggests a different reality. Without careful and effective policy guidance, it remains uncertain whether these colourful dreams of "sustainable AI" will, or should, come true.

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A | Keyword searches for *Sustainability of AI* labelled patents

For constructing the keyword searches, I used two groups of keywords. On the one hand, I used general descriptive words indicating that an AI technology is made more sustainable. On the other hand, I used keywords capturing example technologies along the AI pipeline that likely fall under *Sustainability of AI*. Keywords are listed in Table A.1.

Keywords	**Keywords**
energy-efficient ai	model compression
sustainable ai	pruning
green computing	efficient network
renewable energy for ai	memory utilisation
carbon-neutral ai	edge-based computing
power-aware ai	edge computing
energy-efficient algorithm	data cente
resource-constrained ai	data centre
eco-conscious ai	cooling
environmentally friendly ai	low precision
green machine learning	hardware acceleration
carbon-neutral machine learning	gpu
power-aware machine learning	tpu
energy-efficient machine learning	fpga
resource-constrained machine learning	tensor processing
eco-conscious machine learning	lightweight CNN
environmentally friendly machine learning	sparse computing
energy-efficient hardware	quantization
power-efficient ai	batch optimization
sustainable machine learning	batch optimisation
green neural networks	huffman coding
sustainable deep learning	uninterruptible power supply
energy-efficient inference	data augmentation
environmentally conscious ai	hardware utilisation
green data centers	hardware utilization

Table A.1: Keyword search list to sample *Sustainability of AI* related patents

B | Zero-shot topic descriptions

To analyse how innovation is spread across different elements of the AI pipeline, zero-shot topic modelling was used. For this, pre-defined topic descriptions are required, based on which documents are assigned to a topic. The topic descriptions are listed Table B.1. Note that some experimentation revealed that descriptions based on examples showed much more sensible clustering compared to meta-level descriptions.

High-level overview	**Operations**	**Infra-structure**	**Topic description**
Data collection			sensor, data collection, environmental monitoring, IoT sensors
AI operations	Platform		platform for optimization techniques, framework, library
	Model		algorithmic design, weights, pruned, parallelism, model compression
	Specialised Hardware		computation, specialized acceleration, application-specific integrated circuits, field-programmable gate array
	Infrastructure	Network	network infrastructure, bandwidth, data transmission, routers, cable, switch, firewall, connectivity
		Storage	storage, storage area network, network-attached storage, distributed file system
		General Hardware	data center, uninterruptible power supply, power distribution unit, generator, cooling, ventilation, pump, chiller, low-precision hardware

Table B.1: Zero-shot topic descriptions

C | Environmental impact keyword list

For analysing the environmental impact of *Sustainability of AI* innovation, I used a keyword search. The four main environmental impacts of AI suggested by the literature relate to energy consumption, water consumption, (e-)waste and resource depletion, particularly rare metals which are crucial for many hardware components (Ligozat et al., 2022). Table C.1 presents the list of keywords used to identify the categories which was iteratively adjusted to capture relevant patents in each category.

Impact	**Keywords**
Energy consumption	energy efficiency, low power, energy saving, power reduction, energy efficient, energy-efficient, power efficiency, energy consumption, power consumption, electricity consumption, run time, runtime, efficiency, efficient
Water consumption	water-efficient, water-saving, reduced water use, water consumption
Rare metals	rare-earth-free, alternative materials, reduced metal usage, rare metal, niobium, aluminium, europium, gold, silver, platinum, palladium, tin, tantalum, tungsten, bismuth, cadmium, cobalt, gallium, germanium, indium, lithium, molybdenum, selenium, tellurium, vanadium, zirconium
Waste	recyclable, waste reduction, biodegradable, recycled materials, recycling, re-cycle, waste, toxic, end of life, durability, longevity, extended life, increase lifetime, lifespan, long-lasting, long life

Table C.1: Environmental impact keyword lists