Report on Advances in Digital and Green Technologies

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Abstract

This report presents the development of indicators to track the advancement of digital and green technologies in Europe, utilizing patents as a measure of innovation. It investigates the evolution of patents in three key technological domains—Artificial Intelligence (AI), robotics, and green technologies—using data from the European Patent Office (EPO). By leveraging natural language processing and classification codes, the report identifies technological trends and their adoption across industries.

For digital technologies, the study highlights the growing prevalence of AI and robotics, examining their applications and potential in transforming industrial processes. The green technology analysis focuses on advancements in environmentally sustainable innovations, emphasizing patents tracking technologies for mitigating climate change.

The findings underscore the rapid growth in patent applications and grants within these domains, reflecting the dynamic nature of innovation driven by digitalisation and the green transition. The indicators developed are mapped to relevant industries, providing insights for understanding technology diffusion and its implications for European economies. These insights are integral to the SkiLMeeT project's broader objectives of addressing skills gaps and mismatches in the context of Europe's digital and green transformation.

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1. Introduction

This report presents the content of work package 2.4 of the *SkiLMeeT* project, in which we develop indicators of the advancement of digital and green technologies in Europe based on patent data. The two megatrends digitalisation and green transformation are reshaping European economies and societies on a large scale (Arnold, et al., 2023).

Digital technologies, and Artificial Intelligence (AI) in particular, have been rapidly expanding in capabilities (Maslej, et al., 2024). In combination with established automation technologies like robotics, the possible scope of effects go far beyond traditional technologies. AI is one of the fastest-advancing technological breakthroughs in recent years and is already regarded as a general-purpose technology by some authors (Eloundou, Manning, Mishkin, & Rock, 2024). Even prior to the most recent developments in Large Language Models, AI technologies based on machine learning and neural networks have advanced fast. Robots, in turn, have a longer history of being used in industrial production. However, their potential for automation is strongly increasing and a combination with AI could make robots smarter thereby further enhancing their capabilities (Soori, Arezoo, & Dastres, 2023).

At the same time, climate change and the necessity to exit fossil fuels and reduce CO2 emissions spurs growth in green technologies that are responsible for emission reduction, renewable energy production, and sustainable production. The shift to renewable energy and more sustainability creates new innovation in the field of green technologies (Jayabal, 2024).

In this study, we use patent data to create indicators of the advancement of three key technologies: Artificial Intelligence (AI), Robotics, and “Green” technologies[1].

Measuring and quantifying innovation in these fields is challenging and there are several ways to approximate the growth in digital and green technologies. The usage of patents to study innovation and technological change has a long history and a discussion of the advantages and disadvantages can be found in Griliches (1990), Moser (2013) and Popp (2019) relative to the green part [2]. Some disadvantages of using patent data to identify industry-level exposure to technologies is that our generated measures will be very broad. Further, we can not directly measure the diffusion of the technologies and their implementation in production. Therefore, we need to assume that patented technologies are useful when implemented in production. But using patent data also has significant advantages for us. First of all, in exchange for protection of the intellectual property of their invention,

[1] For the creation of indicators on AI and robotics see also Gathmann & Grimm (2023) and Gathmann, Grimm & Winkler (2024) for an application. Frattini et al. (2024a) and Frattini et al. (2024b) exploit green technologies for identification purposes.

[2] Examples for other authors using patent data to create technology measures are Webb (2020) for AI, Prytkova et al. (2024) for digital technologies, Autor et al. (2024) and Mann & Püttmann (2023) for automation technologies, and Montobbio et al. (2020) for robots.

inventors must make public a detailed description of the invention which allows us to classify each invention. These patents reflect the technological frontier and capture the creation of new knowledge in a field. This varies over industries depending on the production technology used and evolves over time.

Alternative ways to approximate technological change are the usage of R&D expenditures or investments in Information and Communication Technologies (ICT)[3] . Compared to our measure, these approaches are broader, making it difficult to track specific technologies. Another approach is to use data on the actual adoption of technologies like the number of installed industrial robots (Graetz & Michaels, 2018) or the level of manufacturing production that can be defined as green (Vona & Bontadini, 2023). While these measures are very accurate on the specific technology considered, they are usually only available for a smaller set of countries and industries.

2. Identification of AI and Robot patents

We use patents to measure the technological advances in AI and robotics. Patents are granted for major innovations in a given technological field containing detailed information on the additional knowledge or process. Our data covers the universe of patents filed with the European Patent Office (EPO) between 1990 and 2018. The approach proceeds in three steps. First, we prepare the data for applying text analysis to the title and abstract describing each patent. In the second step, we use natural language processing techniques to identify patents in robotics and AI technologies. In the last step, we match the identified patents to the industries most likely to use them in their production process. We now describe each step.

We use data on all patents granted by the European Patent Office (EPO) between 1990 and 2018, which we extract from the World Patent Statistical Database (PATSTAT). Any invention a firm wants to have protected in the European market will be patented at the EPO even if the innovation occurred abroad. The patent documents include the title and abstract of each patent, the name, company, and location of the inventor, the dates of application, and the grant of the patent. The technical content of a patent is categorized by its International Patent Classification (IPC) or, more recently, Cooperative Patent Classification (CPC) codes, which are detailed classifications with several thousand entries. These codes are assigned by highly specialized experts, the patent examiners. To identify patents covering innovations in the field of AI or robotics, we analyse the titles and abstracts of a patent. Though each patent document includes a title, abstracts are missing for about 30% of the patent grants. In that case, we use the IPC/CPC code from the narrow or extended patent family to describe the technical content of a patent. Using this procedure, we can impute two-thirds of the missing abstracts. We then convert

[3] See for example Bloom et al. (2014) or Bresnahan et al. (2002).

all patent abstracts and titles to text corpora using the following pre-processing steps: we convert all text to lowercase, then remove numbers, special characters, punctuation, and stop words. Next, we strip the text of any blanks and white spaces. Finally, we extract word stems and divide the text into tokens.

We use a combination of patent classification codes (IPC/CPC) and keyword searches of the patent title and abstract to identify patents related to robotics and AI. For robots, the technology is clearly defined. The ISO 8373 definition defines a robot as an “actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks”. Robots are further grouped into industrial or service robots based on their intended application. We identify robotics patents if they belong to the CPC code B25J9: “Programme-controlled manipulators”; or if they match a keyword search conducted over the titles and abstracts of all patents. Unlike robotics, AI is a very broad concept that spans multiple technologies. In the context and time of our study, inventions in the field of AI are mostly based on machine learning, neural networks, expert systems and their respective applications in fields like speech or image recognition. One example is level 4 and 5 autonomous driving, which relies heavily on AI-driven image recognition.

We identify AI patents in several steps. First, we use all IPC/CPC codes that are directly connected to a specific AI technology or sub-field like machine learning, neural networks, or fuzzy logic using a list of AI-specific IPC/CPC codes from the World Intellectual Property Organization (2019). An example is code G06N7/046 ‘Computer systems based on specific mathematical models - implementation by means of a neural network’. However, there are only a few IPC/CPC codes for software or algorithms, and most AI-related inventions are not identified by these codes. Many AI innovations are instead embedded in patents in other technology fields which we capture using a keyword search. over the titles and abstracts of all remaining patents based on a keyword list compiled by the World Intellectual Property Organization (2019) and Baruffaldi et al. (2020). Examples of keywords include machine learning, natural language processing, fuzzy logic, or decision tree. The keyword list is pre-processed using the same steps as for the patent documents. A patent is classified as a match for AI technologies if one or more keyword tokens match with tokens of the text corpora of titles and abstracts. Patent titles often include specific terms like neural networks, while the abstract contains more general technological concepts such as artificial intelligence or machine learning.

2.1. Descriptive Statistics of AI and Robot patents

For robotics, our search yields 14,235 patent documents of which 92% contain one or more of the keywords and 8% are included based on the CPC code ‘B25J9’. Around 11,000 are actual applications or grants; the remainder contain supplementary information to existing applications. For AI technologies, the combined approach of codes and keyword search yields 10,311 patent documents of which 90% contain one or more of the AI-specific keywords and 10% are included purely on their CPC codes. After excluding supplementary documents, we are left with around 7,000 applications and grants. To provide first descriptive evidence in which sectors of the economy AI and robotics innovations are patented, we aggregate patents to broader technology classes.

Panel (A) in Figure 1 shows that AI patent grants started to emerge in the mid-1990s but remained low until 2015. Patent applications for AI technologies shoot up after 2015, especially in 2017 and 2018.

Panel (B) of Figure 1 shows the evolution of robotics patent grants and applications between 1990 and 2018. Robot patents show a first peak in the mid-1990s and then again in the late 2000s. Patent applications for robotics continue to grow throughout the whole period.

To check in which sectors of the economy innovations in AI and robotics occur, we use a mapping of IPC codes to thirty-five technology classes following Schmoch (2008) and aggregate them to five broad technology classes: Electrical engineering, mechanical engineering, instruments (e.g., optical instruments, control technology, and medical technology), chemistry (e.g., pharmaceuticals, biotechnology, food, and materials) and other (e.g., many consumption goods like furniture, but also civil engineering). Figure 2 shows that AI technologies are most prominent in electrical engineering but have recently become more important in instruments and mechanical engineering. Figure 3 shows that robotics technology is heavily concentrated in mechanical engineering (see Panel (A)). In recent years, robotics have become more prevalent in instruments and others, which points to new applications beyond mechanical engineering and industrial robots.

3. Identification of Green patents

We use green patents as a proxy to measure advancements in environmentally sustainable technologies. These patents reflect innovations that contribute to mitigating climate change or adapting to its effects. To construct this measure, we exploit data on patent applications submitted to the European Patent Office (EPO) between 1985 and 2018, extracted from the PATSTAT database. This database provides detailed information on patent classifications, facilitating the identification and tracking of green technologies.

We identify green patents using the Y02 classification within the Cooperative Patent Classification (CPC) system. The Y02 classification, introduced in 2010 by the EPO, has been used by international organisations such as the World Intellectual Property Organisation (WIPO) and the Organisation for Economic Co-operation and Development (OECD) (Angelucci et al. 2018).

The Y02 classification encompasses a broad range of technologies aimed at mitigating or adapting to climate change. Subcategories within the Y02 system cover diverse domains such as transportation (Y02T), energy (Y02E), waste management (Y02W), and more. These classifications are designed to highlight environmentally relevant innovations, making it easier to track developments in technologies that address climate change challenges. It is important to note that the Y02 classification does not replace existing CPC codes but rather complements them. For instance, a patent related to combustion engines might be classified under the F02C CPC class but would also receive a Y02T classification if it involves technologies aimed at reducing greenhouse gas emissions in transportation.

This dual classification system allows researchers to distinguish between green and non-green patents within the same CPC class. For example, in the F02C CPC class, which covers gas turbines, green patents could involve innovations in renewable energy integration, while non-green patents might focus on conventional combustion technologies. This nuanced tagging enables a more detailed analysis of technological advancements and their environmental implications.

To quantify the level of greenness within technological fields, we compute an indicator that captures the proportion of green patents relative to the total number of patents within a given CPC class and time frame. Formally, we define this measure as:

$$Greenness_{i,t} = \frac{Green\ Patents_{i,t}}{Total\ Patents_{i,t}}$$

where *i* represents a 4-digit CPC class and *t* denotes the time period. This metric provides a forward-looking perspective on the greening of technological advancements. It allows us to evaluate how specific sectors, countries, or regions are progressing in their efforts to adopt sustainable technologies.

Furthermore, green patent data can be used to compute patent stocks, which are cumulative measures that better reflect the existing know-how in green technologies (Wang & Hagedoorn, 2014; Brunel, 2019). These stocks account for the knowledge accumulated over time, offering a more comprehensive perspective on the sustained efforts and cumulative innovations within the green technology space. Such measures are instrumental for understanding the trajectory of technological transitions toward sustainability and for designing policies to support green innovation.

3.1. Descriptive Statistics of Green patents

Figure 4 reports the evolution of frequency of green patent applications and the greenness indicator over time. Both numbers refer to inventors based in the EU + the United Kingdom, Switzerland and Norway. The number of green patent applications has been rising steadily over time, as well as the share of green patents within CPC classes. Notably, both variables do not show a particular reduction around the 2008 global financial crisis.

We then focus on stylized facts related to green patents and EU countries. Cumulatively, the median EU country hosts inventors that file about 623 green patents, with a greenness indicator of 10.36, while countries corresponding to 25th and 75th percentiles produce 144.5 and 7551 green patents, with values of the greenness indicator of 8.89% and 12.38%. Figure 5 reports the number of green patent applications (left) and the greenness indicator (right) by EU countries. Focusing on the left sub-figure, Germany is the clear EU leader in terms of green patents applications, followed by France, Italy, Netherlands, Switzerland, Sweden and Denmark. Notably, the distribution is quite skewed. Moving to the right sub-figure, the greenness indicator exhibits a more homogeneous distribution, with average greenness that varies roughly between 20% and 8%. Interestingly, Germany can be found at the right end of the chart, suggesting that the driver of the left sub-figure is mostly a size effect. This is true for Italy and France as well. Denmark however is still found on the left end of the graph.

Lastly, we focus on descriptive facts related to green patents and 4-digit CPC classes. The median 4-digit CPC class contains 130 green patents and exhibits a greenness indicator of 3.48, while CPC classes corresponding to 25th and 75th percentiles contain 20 and 613 green patents, with values of the greenness indicator of 1.16% and 11.14%. Moreover, Figure 6 reports the number of green patent applications (left) and the greenness indicator (right) by 4-digit CPC class. For the sake of space, we report the top fifty 4-digit CPC classes by greenness. Focusing on the left sub-figure, the leading classes relate to electric elements (H01L - Semiconductor Devices; Electric Solid-State Devices Not Otherwise

Provided For; H01M - Processes or Means, e.g., Batteries, for the Direct Conversion of Chemical Energy into Electrical Energy), separation technologies (B01D - Separation), human necessities (A61K - Preparations for Medical, Dental, or Toilet Purposes), electric vehicles (B60L - Propulsion of Electrically-Propelled Vehicles) and process chemical and physical processes related to catalysis (B01J - Chemical or Physical Processes, e.g., Catalysis or Colloid Chemistry; Their Relevant Apparatus). Within the top fifty 4-digit CPC classes, the distribution is somewhat less skewed. Moving to the right sub-figure, the greenness indicator signals a few CPC classes that are mostly entirely composed by green technologies. These relate to geothermal energy (F24T - Geothermal Collectors; Geothermal Systems), solar energy (F24S - Solar Heat Collectors; Solar Heat Systems), wind energy (F03D - Wind Motors), liquid-driven machineries (F03B - Machines or Engines for Liquids) and nuclear energy (G21D – Nuclear Power Plants).

4. From patents to industries of use

So far, we have identified patents in AI, robotics and green technologies and have tracked their evolution over time. However, to ultimately estimate the effects of these technologies in production, we need to map them to the industries where they are most likely to be used instead of the industries where they were invented. Those two need not be the same, for example when AI-powered solutions are developed in the IT sector but are ultimately used in manufacturing. Ultimately, the number of patents per industry of use serves as a proxy measure for the usage of the specific technology in each industry.

To map our patents to industries of use, we apply a probabilistic walkover developed by Lybbert & Zolas (2014). Starting from a description of the activities in an industry given by the official classification, a keyword search matches industries to patents if the industry's activities share one or more keywords with the patent description. The result is a list of patents with their IPC/CPC codes linked to industries producing with the knowledge embedded in the patent. The match frequency is used to calculate a probabilistic weight for each industry. The weight is based on Bayes' rule, taking into account the number of possible codes and how often a code is matched to an industry. Patents are then assigned proportionally to industries of use.

5. Outlook

The data produced as output in this work package consists of three measures ultimately that each represent the number of patent grants or applications per year in one of the three technologies AI, robotics, or 'green' at the 3-digit ISIC rev. 4 industry level. Each measure is developed using the same crosswalk to industries of use (Lybbert & Zolas, 2014).

These indicators have multiple potential use cases for the other work packages of the SkiLMeeT project. Here we are going to outline two possibilities for each technology.

The indicator on digital technologies can be used in Task 4.1 which investigates the effect of digitalisation, globalisation, and supply factors on the skills used at work across countries. Further, the data will be used in Task 4.2 to investigate how digitalisation drives the skill needs of employers in Europe. Here, the indicators are used to analyse to what extent skill needs and potential gaps between skill needs and skill supply are explained by advances in digital technologies.

The measures of green technologies will be used in Task 4.3, that identifies the skills needs of firms engaged in green production and innovation activities and potential skills shortages in regional labour markets, and in task 4.4, that conducts an analysis on of the skills requirements and reskilling needs across EU sectors and countries by jointly analysing skills supply and demand.

Figures:

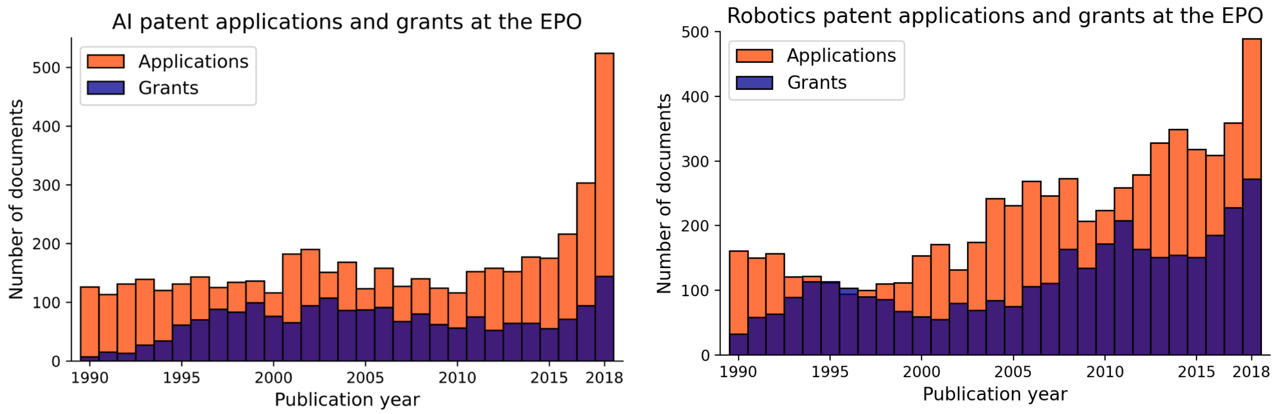

Figure 1: Evolution of AI and Robot patents

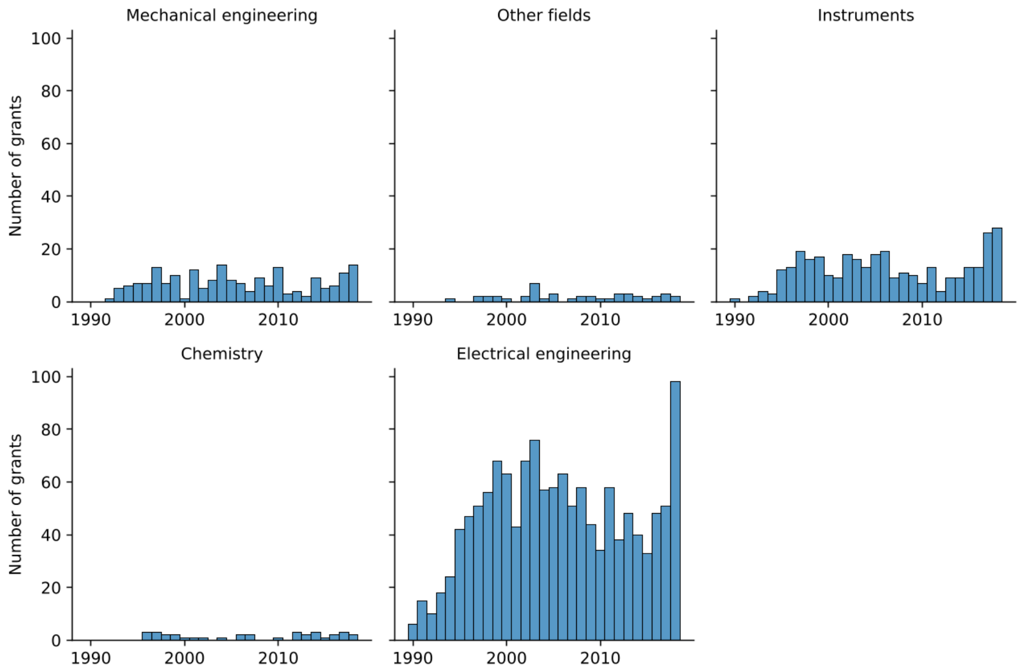

Figure 2: AI patents by technology class

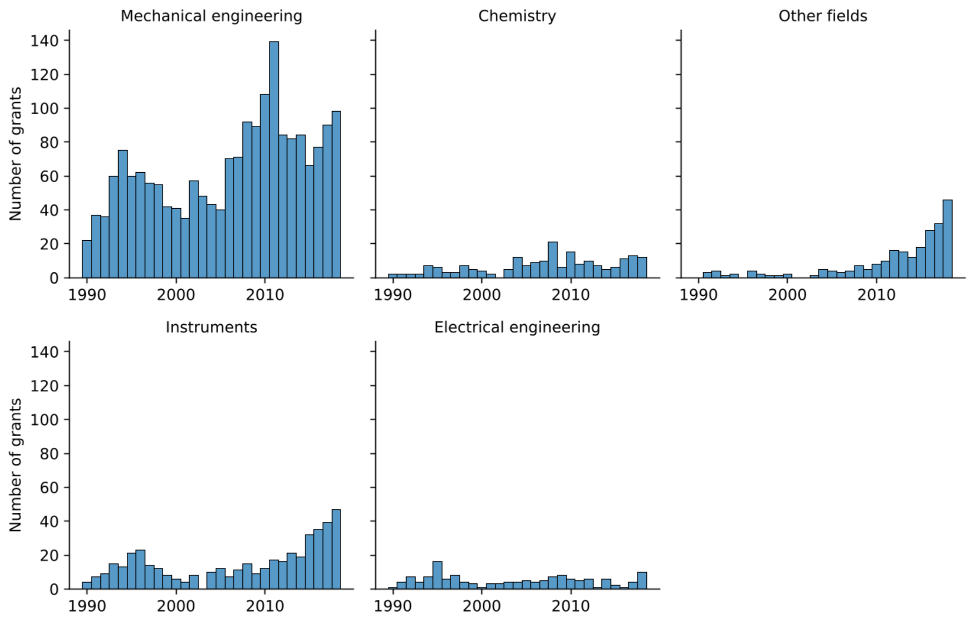

Figure 3: Robot patents by technology class

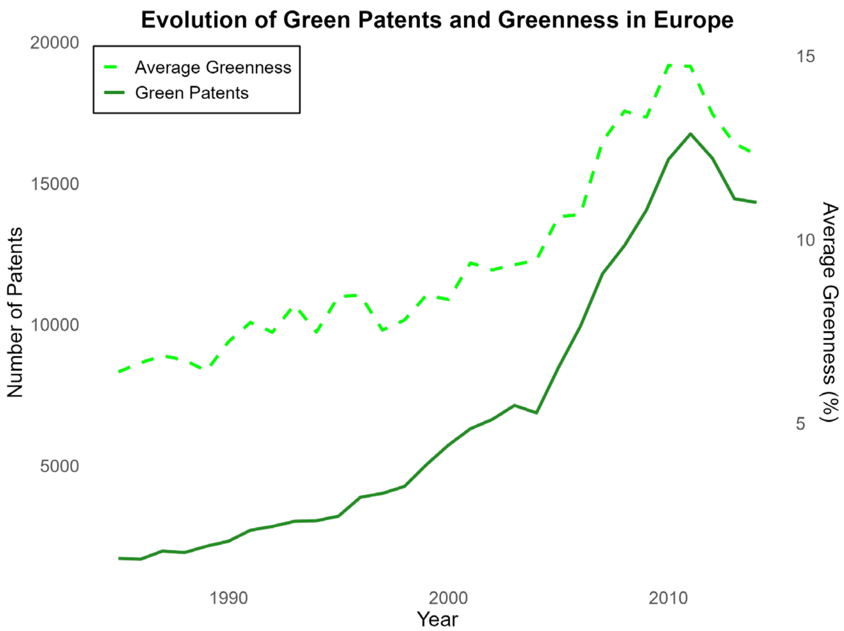

Figure 4: Evolution of Green Patents

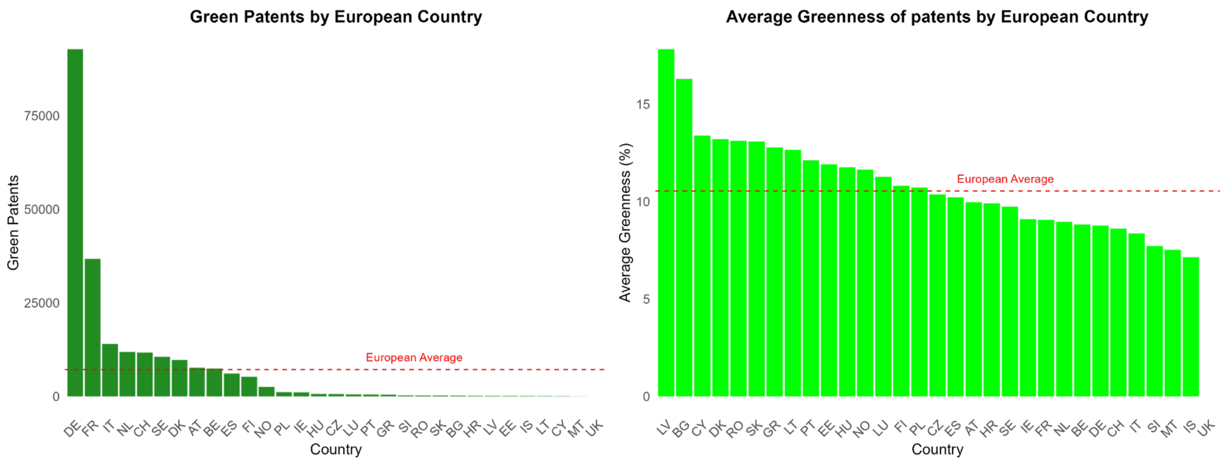

Figure 5: Green Patents by Country

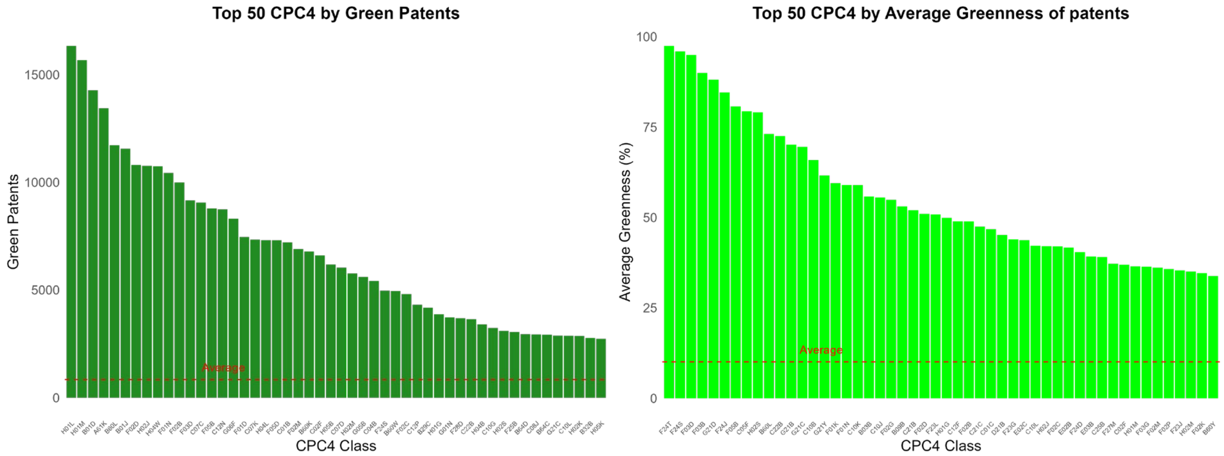

Figure 6: Top CPC codes Green Patents

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