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Green Intelligence: The AI content of green technologies

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Green Intelligence: The AI content of green technologies

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Abstract

This paper investigates the contribution of Artificial Intelligence (AI) to environmental innovation. Leveraging a novel dataset of USPTO patent applications from 1980 to 2019, it explores the domain of Green Intelligence (GI), defined as the application of AI algorithms to green technologies. Our analyses reveal an expanding landscape where AI is indeed used as a general-purpose technology to address the challenge of sustainability and acts as a catalyst for green innovation. We highlight transportation, energy, and control methods as key applications of GI innovation. We then examine the impact of inventions by using measures and econometric tests suitable to establish 1) how AI and green inventions differ from other technologies and 2) what specifically distinguishes GI technologies in terms of quality and value. Results show that AI and green technologies have a greater impact on follow-on inventions and display greater originality and generality. GI inventions stand out even further in these dimensions. However, when we examine the market response to these inventions, we find positive results only for AI, indicating a mismatch between the technological vis-à-vis market potential of green and GI technologies, arguably due to greater uncertainty in their risk-return profiles.

Keywords: Artificial Intelligence, Environmental innovation, Green Intelligence (GI), Twin transition, Digitalization, Green technologies
JEL Classification: O31, O33, Q55, Q56

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1 Introduction

The urgent need to limit the rise in global temperatures requires a comprehensive transition towards a sustainable and low-carbon future (IPCC, 2018). The importance of achieving a net-zero transition is underscored by the robust evidence now available on the escalating impacts of climate change, from extreme weather events to ecosystem losses (IEA, 2021). As nations around the world consider ambitious climate targets, decoupling economic growth from carbon emissions becomes imperative. Central to this objective is the convergence of environmental protection and technological innovation, with digital technologies emerging as important catalysts of the net-zero transition. Among the relevant digital technologies, Artificial Intelligence (AI) is expected to help mitigate urgent environmental problems in different contexts (Vinuesa et al., 2020; Tomašev et al., 2020; Ardabili et al., 2020). As a general-purpose technology (GPT), AI can be adopted for multiple purposes in a broad range of sectors, and – when used as a research tool – even generate new waves of inventions with the potential to create widespread economic impacts (Trajtenberg, 2018). Researchers and companies are indeed "hoping to leverage AI to address one of the most pressing concerns of the modern era".[1] In practice, companies are engaging in new projects to leverage AI algorithms for developing and improving green technologies, seeking the so-called "Green Intelligence". One example is Microsoft's initiative "AI for Earth", a huge commitment to finance projects and harness AI to solve global environmental challenges in key focus areas of climate, agriculture, water, and biodiversity conservation.

Through AI algorithms and machine learning, firms could radically transform their products and processes to achieve greater organizational efficiency and flexibility. For example, these techniques can be easily applied in smart grid management to reduce energy production and waste. Furthermore, AI technologies are enablers of change because they can help to incorporate eco-design principles into new product development, optimize heating and cooling systems in production plants, and re-engineer whole processes for efficient waste disposal.

It must also be stressed, however, that despite the potential to improve the efficiency and environmental impact of production and distribution processes, AI technologies could also lead to higher demand for computing power, higher carbon emissions, unanticipated changes in electricity demand patterns, and an accelerated depletion of natural resources (Brevini, 2023). Indeed, ongoing policy and scholarly debates are very concerned as to whether AI will have a positive or negative environmental impact and, as these concerns grow quickly over time, there is a call for new regulations against a backdrop of technological uncertainty (Swiatek, 2024).

This suggests the need to develop better ways to identify, measure, and characterize AI innovations in technologies capable of positive environmental impacts. As a GPT and arguably the most disruptive among all digital technologies (Martinelli, Mina, and Moggi, 2021), AI can, in principle, provide considerable support to green innovations and their diffusion. However, there is a lack of comprehensive evidence on the green inventions that rely on AI technologies –

[1] https://impact.economist.com/perspectives/sustainability/green-intelligence-ai-could-boost-efforts-fight-climate-change [Last accessed June 27, 2024].

Green Intelligence (GI) inventions hereafter.

The interaction between green and digital technologies has sparked growing research interests in the so-called ”twin” (green and digital) transition (Diodato et al., 2023). Existing studies in this area have primarily examined its antecedents (Montresor and Vezzani, 2023), environmental impact (Bianchini, Damioli, and Ghisetti, 2023), and implications for employment (Santoalha, Consoli, and Castellacci, 2021). This literature has described the emergence of a twin transition at the regional level (Damioli, Bianchini, and Ghisetti, 2024; Fazio, Maioli, and Rujimora, 2024) and demonstrated that digital skills foster the development of circular economy technologies in European regions (Fusillo, Quatraro, and Santhià, 2024). The limited research exploring the twin transition at the firm level has predominantly treated green and digital technologies as distinct entities, even when jointly adopted (see, e.g., Cattani, Montresor, and Vezzani, 2023). However, these studies have largely overlooked the identification of ”twin” (green-digital) inventions. In this paper, we map the landscape of GI technologies, as the most promising subset of “twin” inventions, and document whether and how AI contributes to the development of green innovations. We start by identifying the main application domains and the most common AI techniques applied to green inventions. We then focus on the most important companies developing GI technologies and examine their geographical distribution compared to other AI and green technologies. Finally, we explore the quality of inventions by designing and implementing econometric tests suitable to establish whether GI inventions are more impactful and valuable than other AI and green technologies.

To provide a precise picture of the GI technology landscape, we leverage a unique patent dataset identifying both green and AI technologies. We focus on AI technologies rather than broadly defined digital technologies on which the literature has focused so far. To this end, we combine the World Intellectual Property Organization (WIPO) classification for Artificial Intelligence (WIPO, 2019) with the OECD Env-Tech classification by Haščič and Migotto (2015) for green patents. Applying this search strategy to patent data retrieved from PATSTAT 2023 (Autumn edition), we select 1,249,798 AI and green patent applications filed with the United States Patent and Trademark Office (USPTO) from 1980 to 2019. Despite well-known limitations, patent data are established indicators of innovation activity (Griliches, 1990) and have been extensively used to study the backbone and evolution of technological knowledge (Hall, Jaffe, and Trajtenberg, 2001). They serve as a valuable data source and a reliable proxy that has already been used to analyze trends in both AI (WIPO, 2019; Cockburn, Henderson, and Stern, 2018; Iori, Martinelli, Mina, et al., 2022) and green technologies (Dechezleprêtre, Martin, and Mohnen, 2013; Popp, 2019; Barbieri, Marzucchi, and Rizzo, 2020; Fusillo, 2023) independently from one another. We then combine these data with the OECD Patent Quality Indicators dataset (Squicciarini, Dernis, and Criscuolo, 2013) and the stock market-based indicators of patent value proposed by Kogan et al. (2017) to obtain a multidimensional perspective on the quality of GI inventions.

Our exploratory analyses show a scenario where AI clearly emerges as a catalyst for green innovation, highlighting its potential role in achieving environmental sustainability. We identify transportation, energy, and control methods as critical areas of development for GI innovation, with significant efforts observed in the United States, followed by Japan, South Korea, and China. At the sector level, GI inventions are particularly important for automotive and electronics, suggesting a strategic convergence between mobility needs and advanced electronics in the direction of greener technical solutions. Regarding the quality of GI inventions, we find that the convergence of AI and green technologies is associated with a greater impact on further inventions as measured by forward citations. Moreover, green, AI, and GI patents are all more original and general than other patents, thus confirming their GPT features. However, when we inspect the value of patents by using Kogan et al., 2017's ex-ante market value indicator, we find positive and significant results for AI technologies, negative and significant results for green technologies, and non-significant results for GI technologies. These differences are arguably due to greater perceived uncertainty and lower expected returns for green technologies. A direct comparison of GI technologies with AI and green technologies reveals that GI technologies display higher citation impacts, originality, and generality, but no higher (ex-ante) value, suggesting the existence of a gap between the pace of technological progress and market perceptions.

The remainder of this paper is structured as follows. Section 2 provides an overview of AI in environmental technologies. Section 3 describes data and methods. Sections 4 and 5 report our exploration of the GI patent landscape, and section 6 concludes.

2 The role of AI in environmental innovation

The economic significance of AI lies in its foundational role in spurring technological advancements while also influencing industrial dynamics (Cockburn, Henderson, and Stern, 2018). Considered the latest exemplar of General Purpose Technology (GPT), AI and related methodologies - spanning machine learning, natural language processing, and data analytics - exhibit strong complementarities with other innovations, driving systemic change and altering the entire competitive landscape. A recent WIPO report (WIPO, 2019) reveals an explosive growth in AI inventions, pointing to the technology's widespread adoption and integration into various domains, including environmental technologies (Vinuesa et al., 2020; Swiatek, 2024). Environmental (or green) technologies, embody a variety of innovations designed to mitigate or adapt to changing environmental conditions, enhance resource efficiency, and adhere to environmental standards (Sun et al., 2023). Previous literature highlights that green technologies have a larger and more pervasive impact on future inventions (Barbieri, Marzucchi, and Rizzo, 2020). Considering the nature of AI as GPT (Martinelli, Mina, and Moggi, 2021), the integration of AI into green technologies is expected to enhance the impact of these technologies further. In addition, sinceKogan et al., 2017 show that the market response to the grant of a patent is positively associated with its impact, proxied by the number of future citations, all these technologies should also be associated with higher value. However, it should be considered that emerging technologies may initially face a less positive short-term market response due to uncertainty and perceived risks associated with new innovations. All in all, we expect the integration of AI in green technologies to ultimately gain a higher positive response from the markets as their combined potential and long-term benefits become more evident. The unique combination of AI capabilities with green technologies can lead to innovations that address not only critical environmental challenges but also drive economic growth through increased efficiency and new market opportunities (Cowls et al., 2023).

Despite the growth of scholarly efforts aimed to identify direct and indirect effects of green innovation across sectors and regions (Crespi, Ghisetti, and Quatraro, 2015; Ghisetti and Quatraro, 2017) and combined effects in association with digital technologies (Bianchini, Damioli, and Ghisetti, 2023), systematic evidence on the specific contributions of AI to environmental technologies is scant. Illustrations of these contributions include innovations in environmental monitoring, renewable energy optimization, and AI-based greenhouse gas reduction applications. For instance, among others,(Robinson, Dilkina, and Moreno-Cruz, 2020) study a simulation model based on AI to predict the impacts of climate-induced migration. Rolnick et al. (2022) identify, instead, machine learning's potential to impact solutions across energy systems and ecosystem management significantly, a sentiment echoed by the International Energy Agency (IEA, 2021), which highlights AI's role in enhancing energy efficiency and supporting the shift to renewable energy through smart grids and demand forecasting. An example of this potential impact is a technology developed by Siemens that uses AI-driven solutions to optimize energy distribution and consumption through smart grids. This AI system analyzes vast amounts of data to make real-time decisions on energy distribution, thereby balancing supply and demand, reducing energy waste, and enhancing the grid's reliability. Similarly, IBM has harnessed AI to promote sustainable agriculture. IBM AI-powered tools assist farmers in making data-driven decisions regarding crop management, using data from weather stations, satellite imagery, and Internet of Things (IoT) sensors. These tools enable precision farming, which reduces waste and environmental impact by optimising the application of water, fertilizers, and pesticides. This application of AI in agriculture not only improves yield but also enhances resource efficiency and helps farmers adapt to changing climatic conditions (for an example of patented technology in this field, see Figure A1).

AI's transformative impact extends to climate prediction and modelling, where advanced techniques have markedly improved the processing of large datasets, thereby increasing the accuracy of climate projections and deepening our understanding of climate dynamics. Among other techniques, convolutional neural networks have been used to analyze satellite imagery to gain new insights into deforestation, urbanization, and ecosystem changes (Reichstein et al., 2019) (for an example of patented technology in this field, see Figure A2). In agriculture, AI-driven tools optimize resource use, water conservation, and carbon footprint reduction (Kamilaris, Kartakoullis, and Prenafeta-Boldú, 2017). Expanding the scope of AI's impact, Verendel (2023) perform an extensive analysis of over 6 million US patents to explore AI's role in climate-related innovations, identifying significant contributions in transportation, energy, and industrial production. This study highlights AI's catalytic effect on generating subsequent inventions, with climate patents incorporating AI linked to a considerable increase in technological advancements. In a similar line of research, Li et al. (2023) provides a spatial analysis of climate-related patents in China that reveals the dominance of eastern provinces in innovation and suggests policies to spread clean technology and tailor technical support, highlighting the importance of geographical factors and network dynamics in the diffusion of AI-enhanced climate technologies.

Our study provides a broader assessment of the technologies leveraging AI for green and environmental purposes. The intersection between AI and green technologies is, indeed, a domain largely under-explored in current research. Unlike previous analyses, which use digital innovations as a very broad category of enabling technologies, we take AI apart from other digital technologies and focus sharply on AI and its subcomponents. This approach allows us to uncover specific areas where integrating AI algorithms with green technologies creates innovative solutions to address environmental challenges (Swiatek, 2024). This intersection leverages the capabilities of AI to enhance the efficiency, effectiveness, and scalability of green technologies, thereby fostering sustainable development. In what follows, we will refer to these technologies as Green Intelligence (GI).[2]

3 Data and methods

3.1 Sample construction

Our empirical analysis is based on a dataset of AI and green patent applications filed at the United States Patent and Trademark Office (USPTO)[3] from 1980 to 2019 and retrieved by PATSTAT 2023 (Autumn edition). Due to the recent emergence of GI inventions, we consider patent applications because, contrary to granted patents, they allow us to capture more recent trends in this technology. However, since the USPTO does not consistently report patent applications before 2001, we also perform our analysis on the sub-sample of granted patents.

To identify AI and green patents, we rely on two well-established classifications, namely the WIPO classification for Artificial Intelligence WIPO (2019) and the OECD Env-Tech Classification (Haščič and Migotto, 2015) for technologies with positive environmental outcomes. Both classification schemes use the technology classification codes assigned to each patent – the International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes – to detect inventions in the sector of interest. The WIPO classification for AI identifies the

[2] It is worth noticing that the term "Green Intelligence" has been used in other domains with different meanings (see, for instance, Laurent, 2008; Soleimanpouromran and Ahmadimoghadam, 2021; Juo and Wang, 2022). In this paper, we follow the definition provided by the Economist (see Section 1 and Footnote 1).

[3] We focus on USPTO patents because, in this legislation, it is possible to patent software inventions, contrary to what happens in other patent offices.

use or definition of AI algorithms in inventions by integrating technology codes (e.g., Y10S706 – "Data processing; artificial intelligence" and subcategories of G06N – "Computing arrangements based on specific computational models") with a keyword-based search to collect patents referring to new AI techniques that may lack specific classification codes (e.g., deep learning). The resulting dataset comprises 794,588 green inventions and 142,032 AI patents, as reported in Table 1. While green patents include climate change mitigation technologies with applications to several sectors (e.g., transportation, energy, and building) and inventions for environmental management, AI technologies refer to the application of AI algorithms (e.g., machine learning and expert systems) to various settings. We then consider the intersection between AI and green patents to identify GI inventions, i.e. the application of AI-based software to green technologies. Only a small fraction of green and AI patents (7,166) belong to both sets and have been classified as GI inventions. They represent about 1% of green patents and 4.8% of AI patents.

For all patents in our dataset, we also retrieved information about patent applicants and identified 483,747 different applicants according to the OECD Harmonised Applicant Name (HAN) database.

Table 1: Dataset composition

Period of analysis	1980-2019
# of patent applications	8,995,626
among which:	
# AI patent applications	141,632
# Green patent applications	792,330
# GI patent applications	7,158
# of granted patents	6,959,125
among which:	
# AI granted patents	105,518
# Green granted patents	602,435
# GI granted patents	5,263
# Patent applicants	483,747

GI patents firmly rely on both AI and green technologies. Assuming that patent backward citations map inventions' sources of knowledge, patents cited by GI inventions primarily belong to green (26.8%) and AI (22.9%) technologies, signalling a predominant role of these technologies in GI development and confirming the reliability of our classification. 6% of GI's backward citations refer to other GI patents. The primary reliance of GI on AI and green knowledge is also confirmed when we account for the size of these fields by building a Configuration Null Model (Bollobás, 2001). The models allow us to compare observed backward citations by fields with those expected given the citation-network structure and the occurrence of each field in the sample of patents across time.[4] By comparing the expected number of citations with the observed one, we detect a predominant role of AI knowledge, which is cited by GI patents 16.4 times more than expected in the case where citations were random. The same occurs for green technologies since GI cites green inventions 4.4 times more than expected. The reliance on GI patents is even more evident (83.3 times more than expected), suggesting the emergence of a small but coherent technology field. Interestingly, a general AI patent does not cite green inventions (the ratio between observed and expected citations is 0.46), and green patents do not usually rely on AI inventions (the ratio is 0.26). Since the WIPO classification for AI is based on the identification of AI algorithms, we can conclude that GI inventions are a unique combination of AI and green knowledge resulting in AI algorithms applied to green technologies, as illustrated also by the examples of GI patents reported in Figures A1, A2 A3 in Appendix A. Patent US9898688B2[5] protects a system that analyzes and classifies agricultural conditions, such as water-imposed damage, based on data recorded by one or more drones, relying on a neural network technology applied to precision farming. Patent US11555701B2[6] instead covers a system to auto-determine the height and elevation of a building from the terrain. Such information is used to perform a flood risk assessment. In this case, the underlying invention is a clear example of climate change adaptation technology. Finally, Patent US10318821B2[7] refers to a driver assistance apparatus that supports the navigation of a vehicle with a Stop and Go function controlling the engine. This system is conceived to improve fuel efficiency and reduce the vehicle's carbon dioxide emissions.

To further improve our understanding of GI inventions, our analysis considers subclassifications of AI and green technologies. The WIPO report provides fine-grained patent subclassifications according to the AI technique described or applied in the patent, its functional application, and its application field.[8] AI techniques refer to the AI algorithms described or applied in the patent. They include logical programming for expert systems, fuzzy logic for machine control, and machine learning. Although early AI patents relied on expert systems, machine learning has been the most popular approach in recent years. Since AI technologies have a variety of application settings, the classification of functional applications categorised the operations that can be realised using AI techniques. They include computer vision, control methods for dynamic systems, knowledge representation and reasoning to solve complex tasks, planning and scheduling activities and assignments, robotics, and speech recognition. Finally, AI application

[4] We compute the expected number of GI's backward citations to AI, green, and GI patents by defining 10 random networks that preserve the number of links (citations) of each patent and the application year of each cited invention (to account for the emergence of new fields and citation heterogeneity across time) but assign citations randomly. By averaging the number of citations between fields obtained in these random networks, we define the expected number of backward citations from GI to AI, green, and GI.

[5] patents.google.com/patent/US9898688B2.

[6] patents.google.com/patent/US11555701B2.

[7] patents.google.com/patent/US10318821B2.

[8] See www.wipo.int/tech_trends/en/artificial_intelligence/patentscope.html for more details on the subclassification of AI patents [Last accessed June 27, 2024].

fields describe the invention's sectors of applications.[9] Since AI subclassifications are based on technology codes and keyword searches, each patent could belong to multiple subclasses or none of them. We consider only classes with at least 150 patents to select out relatively unimportant classes and streamline the analysis.

The OECD Env-Tech Classification divides green technologies into six subclasses. They range from technologies for environmental management (including air and water pollution abatement, waste management, soil remediation, and environmental monitoring) and water-related adaptations to climate change mitigation technologies (CCMT) across various sectors such as energy, transportation, building, and carbon capture and storage.

We complement our dataset with a set of patent-level indicators to proxy various dimensions of invention impact and quality. First, we rely on the OECD Patent Quality Indicators (Squicciarini, Dernis, and Criscuolo, 2013) to retrieve measures widely used in the literature. Second, to proxy the private value of inventions, we use the measure of patent value developed by Kogan et al., 2017.[10] The use of this wide range of measures accounts for the multidimensional nature of patent quality (Higham, Rassenfosse, and Jaffe, 2021).

3.2 Variables

To account for the impact and value of inventions, we consider three well-established variables drawn from the OECD Patent Quality Dataset (Squicciarini, Dernis, and Criscuolo, 2013). Our primary dependent variable is the number of forward citations received by patents over a period of 5 years after the publication date. Forward citations are a standard indicator of technological relevance for follow-on innovation and a well-known proxy for patent impact (Trajtenberg, 1990). It is defined as:

$$\text{fwd cit}_i = \sum_{P_i}^{P_i+5} \sum_{j \in J(t)} C_{j,t}, \tag{1}$$

where i is the focal patent, P_i is the publication year, $J(t)$ is the collection of patent applications filed in year t, and $C_{j,t}$ is a dummy variable indicating whether patent j cites i in year t.

We also consider other dimensions of quality (Higham, Rassenfosse, and Jaffe, 2021) by using the originality and generality of a patent as alternative dependent variables. Originality measures the diversity of technological fields on which a patent relies. Following Hall, Jaffe, and

[9] Among others, we identify agriculture, business (including customer service, e-commerce, and enterprise computing), energy management, physical sciences and engineering, industry and manufacturing, life and medical sciences (including bioinformatics, biological engineering, nutrition/food science, drug discovery, and neuroscience), personal devices/computing/HCI, networks (including Internet of Things, smart cities, and social networks), security (including anomaly detection, authentication, cryptography, cybersecurity, and privacy), telecommunications (including computer networks and internet, radio/television broadcasting, telephony, and videoconferencing), and transportation (including aerospace, aviation, autonomous vehicles, vehicle recognition, transportation, and traffic engineering).

[10] The data are available here: https://github.com/KPSS2017.

Trajtenberg (2001), we define originality as:

$$\text{originality}_i = 1 - \sum_{j}^{n_i} s_{ij}^2, \tag{2}$$

where s_{ij} is the share of citations made by patent i to technology class j, considering the set n_i of International Patent Classification (IPC) 4-digit codes assigned to patent cited by i.

Similarly, generality measures the range of technological fields relying on the knowledge codified in the focal patent, reflecting its capacity to enable advancements across multiple technological areas. We can consider generality as an alternative indicator of patent impact since it accounts both for the number of citations and their spread across fields. Generality is defined as:

$$\text{generality}_i = 1 - \sum_{k}^{n_i} r_{ik}^2, \tag{3}$$

where r_{ik} is the percentile of citations received by patent i from the technology class j belonging to the set n_i of International Patent Classification (IPC) 4-digit codes assigned to patent citing i.

We complement this analysis by including the indicator of stock market patent value as defined by Kogan et al. (2017). This indicator captures the stock market response to news about granted patents. By construction, it is available for patents granted by listed companies only. Contrary to previous indicators capturing the technological dimension of inventions' quality, this index adds the market dimension to our technology impact analysis. In this way, our analysis allows us to test both the degree of technological impact and the response and expectations of the market to these emerging technologies.

In the patent quality analysis of AI and green inventions, we also control for the number of backward citations and the number of citations to the non-patent literature (NPL) contained in a patent, patent family size (i.e., the number of patents regarding the same inventions, possibly filed in different jurisdictions), the number of inventors, and the number of claims.[11]

3.3 Methods

To test whether GI inventions have a higher quality and are more valuable than other AI and Green inventions, we rely on an OLS regression to estimate the impact of GI inventions on the different proxies of impact and value we use as outcome variables. Specifically, we estimate the following model:

$$\text{Y}_{i,f,t} = \beta_0 \text{Green}_i + \beta_1 \text{AI}_i + \beta_2 \text{Green}_i \times \text{AI}_i + \chi_i + \gamma_f + \delta_t + \epsilon_{i,t,y}, \tag{4}$$

[11] As the number of claims is available only for granted patents, the analyses including this control variable are performed only on the subset of granted patents.