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Are AI and environmental technology innovations converging?

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ABSTRACT

Artificial intelligence (AI) is increasingly invoked as a means of advancing climate and environmental solutions, yet how it shapes environmental technology (ET) development remains poorly understood. This study addresses that gap by asking: To what extent are AI and ETs converging, and which specific domains are driving this integration? To investigate these questions, we have constructed a new dataset of nearly 8000 AI-environmental (AI-ENVI) patents filed at the USPTO from 2003 through 2023. Drawing on this dataset, we perform semantic reclassification followed by forward citation mapping to identify influential innovations and to evaluate prominent domains of technological convergence. We find that three fields dominate: renewable energy optimization, electric vehicles, and fossil fuel efficiency/industrial decarbonization. To probe further, we examine metrics of novelty, disruptiveness, and generality. Novelty is highest in grid-level energy storage optimization; disruptiveness peaks in blockchain-based energy trading; and generality is strongest in the former as well as energy demand forecasting. Evidence that AI applications for incumbent industries attract high forward citations, and that carbon capture and storage (CCS) emerges as a disruptive subcategory, underscores the need for appropriate policy mechanisms to avoid carbon lock-in within the ET–AI nexus.

1. Introduction

Artificial intelligence (AI) and environmental technologies (ETs[1]) have emerged as two of the most transformative technological domains of the 21st century (Coeckelbergh & Sætra, 2023; Rolnick et al., 2022). While foundational ETs such as electric vehicles (EVs) remain central to the low-carbon transition (Fleiβ et al., 2024), AI is emerging as a catalytic force, accelerating and optimizing solutions across industries (Golombek et al., 2022; Xin et al., 2023). It can help enhance energy system efficiency through solar and wind forecasting (Movsessian et al., 2021), provide real-time emissions monitoring (J. Wang et al., 2024; Q. Wang et al., 2023), augment energy storage systems (Zumofen, 2025), and optimize the use of batteries (K. Liu, Tao, & Bi, 2022). Industry-specific applications span green manufacturing (Mao et al., 2019), EV charging optimization (Attia et al., 2020), industrial process innovation (Chotia et al., 2024), intelligent building management (L. Chen et al., 2023; Manmatharasan et al., 2025), and decarbonization of heavy industry (Hussain et al., 2024)

Further, AI and ETs are attracting substantial public and private investment. In 2023, global public spending on energy R&D reached $50 billion, while corporate energy R&D grew three times faster than global GDP (IEA, 2025a). At the same time, from 2022 to 2024, AI-related firms in the U.S. accounted for 65 % of the $16 trillion increase in S&P 500 market capitalization (ibid).

Policymakers increasingly advocate for a "Twin Transition", which involves coordinated development of digital technologies alongside ETs (Fouquet & Hippe, 2022). This dual transformation carries significant implications not only for the energy transition, but also for industrial organization and patterns of innovation (Acemoglu, 2021; Agrawal et al., 2019). Even though the parallel advancement of digital and ETs presents opportunities for sustainable transformation (Li et al., 2025), it also introduces significant tensions (Stanford University, 2023). As demand for AI technologies accelerates, for instance, it poses potential risks to energy systems and may inadvertently undermine climate goals (Maslej et al., 2025). As a salient example, hyperscale data centers that power large language models (LLMs) now consume electricity in amounts comparable to large cities when being trained and used for inference (Hoefler et al., 2022).

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[1] This article uses environmental technologies to refer to all technologies related to the climate and environment: clean; climate mitigation; climate adaptation; renewable energy; solar energy; wind energy, etc. (see OECD: https://www.oecd.org/en/data/indicators/patents-on-environment-technologies.html).

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Despite the policy and practical importance of the Twin Transition, data-driven analyses of this convergence remain limited. The scarcity of quantitative analyses may, therefore, challenge our ability to inform policy (Q. Wang et al., 2023). Here we quantitatively assess the convergence of one specific, yet critical, digital technology, AI, with ETs. While our analysis provides empirical insight into this intersection, we acknowledge that it captures only one dimension of the broader Twin Transition.

We use patent data as a proxy for innovation. Patents provide a window into technological change, revealing patterns of innovation, sectoral shifts, and the emergence of high-value breakthroughs, particularly for ETs (Herman & Xiang, 2019; Jaffe et al., 2005). Large-scale patent databases such as the USPTO's Artificial Intelligence Patent Dataset (AIPD) map AI diffusion across technological domains, while databases like WIPO GREEN track developments in clean and low-carbon technologies (Toole et al., 2020). More specialized datasets focus on renewable energy patents using advanced text mining (Freunek & Niggli, 2023), and recent work has produced a climate-AI dataset of 4390 patents filed through 2019 (Verendel, 2021).

While these quantitative approaches demonstrate the value of patent-based analysis, most Twin Transition research has emerged from qualitative disciplines such as innovation studies and political economy. For instance Brea (2024) emphasizes the geopolitical and systemic foundations of the Twin Transition (Brea, 2024), while Bianchini et al. (2023) examine how organizational design steers technological trajectories (Bianchini et al., 2023). Others explore absorptive capacity and regional ecosystems as mediators of ET adoption (Cicerone et al., 2023; Kopka & Grashof, 2022), as well as the infrastructural lock-ins constraining sustainable digital transformation (Brevini, 2023; Kaack et al., 2022).

Although qualitative studies help to illuminate the structural, institutional, and organizational conditions shaping the transition, few have sought to quantify the intersection of digital and ETs—or to trace how their convergence unfolds in practice. Responding to this deficit, this study asks the following: To what extent have AI and ETs converged? What are the contours of this convergence? Is this convergence leading to transformative innovation? To address these research questions, we construct a dataset that includes approximately 8000 AI-ENVI patents granted through 2023. We develop a novel LLM to classify the patents into 17 categories and 67 subcategories.

To characterize convergence and its consequences, we move beyond raw citation counts and compute three complementary indicators, building on prior studies (Biggi et al., 2025; Feng, 2020; Jiang et al., 2024; Qi et al., 2020): *generality*, which uses breadth of forward citations across fields, capturing how widely a technology diffuses; *novelty*, which computes rarity of each patent's IPC (International Patent Classification) co-class combinations; and, *disruptiveness*, capturing how follow-on work shifts attention away from a patent's predecessors.

In sum, we contribute the following: (1) a new open-access dataset for AI-environmental research; (2) a mapping of domain-specific convergence trends; (3) one of the first large-scale quantitative assessments of the Twin Transition; and (4) new insights into the governance and coordination challenges emerging at the intersection of digital and environmental innovation systems.

This article proceeds as follows. Section 2 positions our data approach and analysis within the Twin Transition framework, outlining its theoretical and policy relevance, and details patents as a credible proxy for innovation in these domains. Section 3 details the dataset construction methodology. Section 4 presents our semantic classification and analyzes high-value innovation trends. Section 5 interprets the findings through the Twin Transition lens. Section 6 concludes, reflecting on implications for innovation policy and future research.

2. Theoretical and empirical foundations

This section begins by mapping out the theoretical foundation for this work, then discusses patents and innovation for AI and ETs, both jointly and independently, and closes by introducing related patent datasets.

2.1. Analytical framework and policy setting

The Twin Transition now serves as a key framework for interpreting the 21st century's industrial and digital transformation (Adewoyin et al., 2025; Appio et al., 2024; Sareen & Haarstad, 2021). Digital technologies can reinforce green innovation when supported not only by complementary capabilities and skills, but also by governance (Chotia et al., 2024; S. Wang & Zhang, 2025). The Twin Transition, from this perspective, therefore, serves as both an analytical and policy frame. It helps to highlight how digital technologies interact with low-carbon systems to shape decarbonization, resource efficiency, and ecological resilience (Appio et al., 2024; Bianchini et al., 2023; Fouquet & Hippe, 2022).

There are, however, both benefits and risks associated with this transition (Diodato et al., 2023). Bianchini et al. caution that digitalization may worsen emissions outcomes unless co-developed with green capabilities (Bianchini et al., 2023). Sareen and Haarstad warn of rebound effects and the risk of reinforcing incumbent power (Sareen & Haarstad, 2021). Luers et al. highlight the rising energy and material demands of AI systems, which may counteract their potential climate benefits without strong oversight (Luers et al., 2024). Creutzig et al. argue similarly that digitalization is reshaping human–earth relationships in unknown directions by concentrating control and exacerbating energy consumption (Creutzig et al., 2022). Directionality also matters: digital tools can either entrench existing hierarchies or catalyze structural reorientation—paths that will shape the course of sustainability transitions (L. Chen et al., 2023; Hopp, 2025). These considerations therefore raise key questions about institutional capacity and uneven technological change across time and space (Herman & Xiang, 2020; Kus & Jackson, 2025; Rehman et al., 2023).

In response to these dual imperatives, governments are embedding the Twin Transition in national and regional agendas in an attempt to balance AI deployment and safeguard against rebound effects (Chan et al., 2024). The European Commission, for example, has prioritized AI development for energy and mobility systems while raising concerns over digital sustainability and electronic waste (European Commission, 2022). The UK's Climate Change Committee supports AI-driven emissions reductions but stresses the need for regulatory frameworks to manage energy consumption (UK CCC, 2024). In the United States, the Department of Energy has issued sustainability guidelines for AI-driven cloud infrastructure and data centers (USDOE_AI_Energy_2024). Across Asia, diverse approaches are emerging: Japan's Green Growth Strategy emphasizes AI for manufacturing and transport decarbonization (METI, 2022); South Korea's Green New Deal promotes AI in sustainable urban planning (J.-H. Lee & Woo, 2020); and China's 14th Five-Year Plan mandates AI-enabled monitoring of environmental quality (Yin et al., 2022).

These policy efforts underscore a key question: will governance initiatives steer the Twin Transition toward transformative change or simply reinforce incumbent systems? The AI–environment nexus has, indeed, attracted substantial policy and investment attention, yet rigorous evidence on its real-world impacts and distributional consequences remains scarce. Rather than charting the entire Twin Transition, this article focuses on a critical intersection: the convergence of AI and ETs. Although AI constitutes only one dimension of the wider digital transformation, its expanding role in industrial automation, data infrastructures, and environmental monitoring makes it a particularly significant domain for assessing the technological and policy implications of this convergence (Chan et al., 2024).

2.2. Patents and innovation

Patent data provide a valuable lens into technological progress, offering insights into both emerging and maturing sectors (Herman, 2022; Herman & Xiang, 2020; Jaffe et al., 2005). Patent filings signal innovation activity (Archibugi & Pietrobelli, 2003); they also provide evidence of macroeconomic technological shifts (Hall & Helmers, 2019; Pavitt, 2002). While patents capture inventions rather than their market implementation, high-value inventions often translate into broader *innovation impact*. Metrics such as patent citation counts, discussed later in this section, help to identify breakthrough innovations and sectoral transformations (Giczy et al., 2022).

ETs—often referred to interchangeably as environmental, climate, clean, or sustainable technologies—have seen rapid growth as measured by patent activity over the past two decades (Herman & Xiang, 2022a; Johnstone et al., 2010). Spurred on by targeted climate policy incentives and key technological breakthroughs, patenting in areas such as renewable energy initially surged during the early 2000s (Cohen et al., 2020; OECD, 2015). Between 2000 and 2022, low-emissions energy technology patents were four-and-a-half times that for fossil energy, signaling a decisive shift in innovation priorities (IEA, 2025b). This pattern signals a fundamental transformation in both global climate governance and the trajectory of environmental innovation (Fusillo et al., 2022; Solarin et al., 2025).

ETs are shown to draw on diverse and cognitively distant knowledge sources (Hötte & Jee, 2022), exhibiting greater combinatorial diversity by recombining knowledge from disparate domains (Fusillo, 2023; Herman & Xiang, 2022a, 2022b). In parallel, given AI's potential role in this convergence, fostering interdisciplinary collaboration and ecosystem-level learning is essential to ensure that ET inventions move beyond patent portfolios to broader market penetration (Ooms & Piepenbrink, 2021; Orsatti et al., 2020).

Innovation in AI began initially from the early 2000s (Krizhevsky et al., 2012). It experienced a marked acceleration after 2015, fueled largely by advances in machine learning (Lannelongue et al., 2021), and breakthroughs in computer science that accelerated LLMs (Vaswani et al., 2017; Devlin et al., 2019). Availability of large-scale training data also precipitated this rise (Brynjolfsson et al., 2021; Cockburn et al., 2019). Such technological maturation has enabled AI's expanding role in environmental applications in more recent years (Kristian et al., 2024).

While AI patent volume continues rising, the share of highly cited, high-impact patents fluctuates, suggesting that transformative breakthroughs are path-dependent (Habibollahi Najaf Abadi & Pecht, 2020). This aligns with findings that major advances often result from atypical recombinations of knowledge across corporate and open-source settings (Brea, 2024). These recombinant dynamics underscore how institutional diversity within AI ecosystems shapes both the direction and quality of innovation.

Research on USPTO patents from 1980 to 2019 demonstrates that, as AI evolves into a full-fledged general-purpose technology, "green intelligence" applications across transportation, energy, and pollution control are increasingly more likely to arise (Biggi et al., 2025; Zu et al., 2025). Targeted AI-ET convergence is already widely found in solar and wind forecasting (GE, 2022; Memari et al., 2024; H. Wang et al., 2020), optimization of batteries (K. Liu, Tao, & Bi, 2022; Nair et al., 2024), energy-efficient building systems (Manmatharasan et al., 2025; Schneider Electric, 2024), and EV charging infrastructure (Attia et al., 2020). Nevertheless, market responses reveal a disconnect between technological potential and commercial valuation for ETs compared to AI alone (W. Liu, Tao, & Bi, 2022; S. Wang & Zhang, 2025). The success of this symbiosis will ultimately depend on whether adoption patterns, investment priorities, and systemic integration can be directed toward accelerating sustainability transitions.

The elephant in the room is AI infrastructure (Herman & Griffiths, *forthcoming*). Energy-intensive data centers, high-performance chips, and cloud services carry significant environmental costs that may offset the climate benefits of AI (Deloitte Global, 2024; Edwards et al., 2024; Hoefler et al., 2022). This paradox lies at the heart of concerns about AI-ET convergence: while AI offers powerful tools for environmental optimization, its own resource demands could undermine net sustainability gains. The long-term impact of this convergence therefore remains highly uncertain (Di Vaio et al., 2020; Nasir et al., 2023). Resolving these tensions requires rigorous empirical analysis of AI's environmental trade-offs—a research need that remains largely unmet.

2.3. Patent datasets: state-of-the-art

In recent years, several foundational datasets have explored AI innovation. The Artificial Intelligence Patent Dataset (AIPD), developed by researchers at the USPTO, includes 15.4 million patents (1976–2023) and reflects AI's growing entrenchment across industries (Pairolero et al., 2025; Toole et al., 2020). In a different study, Fujii and Managi (2018) extract 13,567 AI patents published between 2000 and 2016 across the U.S., Japan, China, Europe, finding a shift from biological and knowledge-based models toward mathematical and other specialized AI technologies. Verendel (2023) identifies 4390 AI-environment patents (1976–2019), showing that these outperform traditional environmental patents in innovation output (Verendel, 2021). Sector-specific studies show that emerging innovation leaders are not easily detectable with conventional metrics (Freunek & Niggli, 2023). By combining patent family IDs with reclassification systems from the USPTO and PATSTAT, these approaches enable robust longitudinal analysis of climate-relevant innovation trajectories.

2.3.1. Analyzing innovation strengths and trends

Beyond dataset construction, recent advances in machine learning (ML) and natural language processing (NLP) have reshaped how patent data can be analyzed. This has enabled more dynamic tracking of technological convergence and innovation frontiers (Haghighian Roudsari et al., 2022; Trappey et al., 2020). Traditional taxonomies based on IPC codes are increasingly being supplemented or replaced by algorithmic techniques that can identify emerging linkages (Qi et al., 2020), detect novelty patterns (Feng, 2020), and track domain crossovers as they develop (Jiang et al., 2024).

LLMs and embedding-based classifiers now support semantically rich, scalable analyses of technical content (Pelaez et al., 2024; Rodriguez-Sanchez et al., 2025). LLMs can also be used for automated generation and analysis of the text within patent claims, advancing the scalability of analysis (Jiang et al., 2024; Luitse & Denkena, 2021). Using a BERT model, Yu et al. conduct semantic similarity matching, demonstrating strong performance in tracking latent linkages between fast-evolving technology fields (Yu et al., 2024b). PatentBERT has improved search and clustering tasks and can compute patent similarity scores (Bekamiri et al., 2024; Bergman et al., 2023; J.-S. Lee & Hsiang, 2020). ClimateBERT has, similarly, emerged as an important LLM to enhance sustainability-related classification, topic extraction, and metadata enrichment (Webersinke et al., 2022).

Citation-based methods remain foundational as a proxy for high-value *inventions* that translate into *innovation* (Rezazadegan et al., 2024). As demonstrated by Verendel (2023), highly-cited patents (inventions) are indicative of market penetration and technological value (innovations) (Verendel, 2021). He further finds that, within his dataset, a small set of high-impact AI–climate patents account for a large share of forward citations.

One consideration, however, is that citations take time to accrue. Time lags imply that innovative outcomes are not immediately detected. To ameliorate this concern, researchers combine citation metrics with other techniques such as graph embeddings (Choi & Yoon, 2022; Feng, 2020), citation tree structures (Qi et al., 2020), and network-wide similarity scores (Whalen et al., 2020). These metrics help to pinpoint early breakthrough innovations (Byun et al., 2021).

Beyond patent counts and raw citations, widely used patent-quality indicators capture complementary dimensions of technological significance: *generality* (breadth of influence across forward-citing fields), *novelty* (rarity of IPC co-class recombinations relative to historical baselines), and *disruptiveness* (the extent to which follow-on work shifts attention away from predecessors) (Biggi et al., 2025; Higham et al., 2021). After introducing our dataset in the next section, we leverage several of these techniques in Section 4 for deeper analysis.

3. Data and methods

We construct a novel dataset capturing the intersection of AI and ETs to quantitatively assess the state of the Twin Transition. This section first describes the three independent datasets we merge, then details our processing and classification methodology. While the initial dataset spans 1976–2023, we focus our analysis on 2003–2023 given the limited AI patent activity in earlier years and to ensure data quality and completeness.

3.1. Developing the AI-ENVI dataset

We constructed the AI-ENVI dataset from the USPTO Bulk Patent Data (USPTO, 2025) by merging classifications from the Artificial Intelligence Patent Dataset (AIPD) (Pairolero et al., 2025; Giczy et al., 2022; Toole et al., 2020) with the IPC/WIPO Green Inventory (WIPO Green, 2024).

1. **AIPD Dataset:** Initially released by the USPTO in 2021, its 2023 update expands coverage to 15.4 million patents. The researchers leverage transformer-based models such as BERT for Patents (Yu et al., 2024a; Yu et al., 2024b) and active learning-based refinement (Bekamiri et al., 2024; Haghighian Roudsari et al., 2022). This enhances classification accuracy by focusing on patents located near the AI/not-AI decision boundary and adds 2.2 million new patents (2021–2023).
2. **WIPO IPC Green Inventory**: To identify environmentally relevant patents within the AI corpus, we use the WIPO IPC Green Inventory, which maps IPC codes to green innovation domains (WIPO, 2024). It classifies patents into seven areas: alternative energy, transport, energy conservation, waste, agriculture/forestry, regulatory/design aspects, and nuclear energy. Cross-referencing AIPD patents with this inventory allows us to isolate those at the AI–environmental intersection, forming a hybrid AI-ENVI classification that captures both technological and ecological relevance.
3. **USPTO Bulk Patent Data:** This data serves as the foundational source for extracting detailed metadata, including IPC codes, inventor information, abstracts, and citation records (USPTO, 2025). This rich dataset enables the disaggregation of patent-level characteristics and supports the convergence of AI and environmental classification schemes. It provides the technical and bibliometric backbone necessary for longitudinal analysis and trend detection.

3.2. Processing and filtering

To ensure the robustness and validity of the AI-ENVI dataset, we applied a multi-step filtering process that reduced the initial dataset from 7,554,887 patents to a final sample of 10,655 unique AI-environmental patents. This filtering approach isolated high-quality patents at the intersection of AI and ETs while reducing noise from low-impact categories (see also Appendix I, step 7).

- Step 1: Technology subgroups with no granted patents between 2010 and 2017 were excluded, eliminating ~1 % of subgroups likely to reflect dormant or nascent innovation domains.
- Step 2: To focus on recent AI innovation, we restricted the dataset to patents granted from 2003 to 2023. Citation data was similarly limited to this period to maintain consistency.
- Step 3: We retained only granted patents, excluding pre-grant publications, since granted patents are better proxies for validated novelty and commercial relevance. This yielded 7,882,655 patents.
- Step 4: Patents were retained if at least 50 % of their technology codes fell within one of AIPD's eight AI domains (e.g., machine learning, NLP, computer vision), resulting in 1,320,747 AI-aligned patents.
- Step 5: These AI patents were cross-referenced with IPC codes from the WIPO Green Inventory. The final AI-ENVI subset includes 10,655 patents that are both AI-relevant and environmentally classified, each with at least two named inventors.

The next section undertakes a quantitative assessment of our unique AI-ENVI dataset.

4. Dataset exploration

This section begins by training a classification model (Section 4.1), followed by a forward citation analysis (Section 4.2), and closes by conducting deeper analyses of novelty, generality, and disruptiveness (Section 4.3).

4.1. Semantic classification

We develop a systematic categorization framework to map the intersection of AI and ETs, then implement a machine learning-based classification system to automatically categorize the patent dataset according to this framework.

4.1.1. Categorization framework

A structured categorization framework was developed by synthesizing insights from the academic literature on AI in environmental contexts (Kaack et al., 2022; Rolnick et al., 2022; Vinuesa et al., 2020), as well as relevant grey literature and established patent taxonomies (e.g., the European Patent Office's climate-related technology classification). The framework is operationalized via an LLM-driven keyword dictionary (Appendix I), which generates the category and subcategory keyword sets used for tagging (Appendix II).

4.1.2. Categorization delivery

We built a classification pipeline following established methodological approaches (Bergman et al., 2023; Marín-Vinuesa et al., 2020).[2] After removing duplicates and out-of-scope patents, and truncating the dataset between 2003 and 2023, we randomly selected ten percent, or 788 patents, from the remaining 7878 patents for manual labeling. Three domain experts with backgrounds in ET and AI technologies independently validated the labeling scheme and resolved classification disagreements through consensus, achieving inter-annotator agreement of $k = 0.82$ (we withhold expert identities for sake of peer review anonymity).

After a first run of the categorization model, the subcategories of 188 patents could not be determined to fall directly under one subcategory, and were therefore classified as "other." Our final training dataset thus

[2] The classifier was trained on an 80/20 split of the 600 labeled patents, with performance evaluated on the held-out test set of 120 patents. Cross-validation ($k = 5$) on the training data achieved 87.3 % accuracy and F1-score of 0.84, while the independent test set demonstrated 85.8 % accuracy and F1-score of 0.82, confirming robust generalization performance.

Table 1
Main categories.

Categories	Freq.	Percent
AI for Renewable Energy Optimization	1510	19.17
AI for Electric Vehicles	1235	15.68
AI for Fossil Fuel Efficiency & Industrial Decarbonization	1175	14.91
AI for Data Centers & Cloud Computing	700	8.89
AI for Sustainable Industry & Circular Economy	658	8.35
AI for Energy Storage	654	8.30
AI for Environmental Monitoring & Compliance	457	5.80
AI for Energy Grid Optimization	333	4.23
AI for EV Charging Infrastructure	308	3.91
AI for Internet of Things & Smart Devices	282	3.58
AI for Ocean & Water Resource Management	234	2.97
AI for Smart Cities & Energy Efficiency	145	1.84
AI for Agriculture & Land Use	61	0.77
AI for Peer-to-Peer Energy Trading	38	0.48
AI for Disaster Response & Resilience	48	0.61
AI for Climate & Weather Prediction	19	0.24
Other/not classified	21	0.27
Total	7878	100

Table 2
Subcategories (top 20). Note: Sub-Categories occurring less than five times were dropped.

Subcategory	Freq.	Percent
Autonomous EV Optimization	652	10.50
Solar & Wind Energy Production	469	7.56
Air & Water Quality Analysis	446	7.19
Green Manufacturing	438	7.06
Chemical Process Optimization	416	6.70
AI-Optimized Server Management	382	6.15
Hydrogen Fuel Cell Integration	375	6.04
Electric Planes and Drones	309	4.98
Cloud Computing Energy Efficiency	301	4.85
Solar & Wind Forecasting	281	4.53
Smart Grid & Energy Storage	277	4.46
Battery Health Prediction	268	4.32
Hydrogen Technologies	260	4.19
Dynamic Grid Management	243	3.91
Smart Grid Integration for EVs	206	3.32
Smart Device Energy Consumption	197	3.17
Fossil Fuel Energy Efficiency	195	3.14
Material Discovery & Recycling	167	2.69
EV Battery Management	163	2.63
Gas & Oil Extraction Efficiency	162	2.61
Total	6207	100

included 600 manually-categorized patents.[3] Our labeling system organized patents into 17 main categories—such as AI for Renewable Energy Optimization, and AI for Energy Grid Management—and 67 more specific subcategories, such as Solar and Wind Forecasting, Methane Detection, Supply Chain Optimization, and Cloud Computing Energy Efficiency (see Appendix II). Tables 1 and 2 show the initial categorization results, along with statistics for categories and subcategories, respectively. Fig. 1 depicts the top five categories and their patent counts over a 21-year period. The robustness checks detailed in the Appendix confirm that our filtering criteria did not systematically bias results toward particular technological domains or assignee types.

4.2. Forward citations

As outlined in Section 2.3, forward citations indicate technological relevance by capturing how much a patent contributes to subsequent innovation (Feng, 2020; Qi et al., 2020). To identify influential innovations at the intersection of AI and ETs, we conducted a comprehensive forward citation analysis following established practices (Fredström et al., 2021; Nesta_asf_core_data_2024; Patterson & Teh, 2013; Petrakis, 2023/2023). Specifically, we developed a custom analysis protocol to assess citation patterns using USPTO's PatentsView API (USPTO, 2025; Whalen et al., 2020). Patents were processed in batches of 50 with intermediate outputs saved to ensure reproducibility and data integrity. The minimum citation threshold was set at 15 forward citations to focus on patents with demonstrated technological impact. See our GitHub repository for complete implementation details.[4]

For each patent, we calculated multiple forward citation metrics to capture different dimensions of technological influence: Forward citation count represents the volume of forward citations received by a patent. Citation span measures the duration in years from patent publication to the most recent citing patent. Recency ratio quantifies the proportion of citations received in the most recent years relative to the patent's age, indicating whether a patent maintains sustained relevance over time (Table 3). The analysis also produced detailed citation linkage data and summary statistics by IPC class and filing year to identify temporal trends in AI-environmental innovation activity. This approach enables identification of both historically important patents and emerging technologies with high future potential.

4.3. High value innovations in AI-ENVI

We examine the 1000 most-cited AI-environmental patents to identify which subcategories have the greatest technological influence. Forward citations serve as our impact proxy, enabling technology forecasting, R&D prioritization, and policy focus. To address biases in raw citation counts—including patent age, field effects, and assignee scale—we employ multiple quality metrics beyond citation volume, such as citations per year and normalization within application year cohorts (Tables 4 and 5). Fig. 2 shows the normalized citations of the top five categories.

4.3.1. Analyzing innovation strengths and trends

Rounding out our analysis, finally, we measure three dimensions of patent quality: (i) *novelty*, (ii) *disruptiveness*; and (iii) *generality*. These complementary measures distinguish patents that are merely “often cited“ from those that are “field-spanning,“ “recombinantly innovative,“ or “paradigm-shifting,“ providing a nuanced view of technological impact across AI-environmental domains (Biggi et al., 2025). Calculations are shown in Appendix III.

This framework distinguishes subcategories with narrow but transformative innovation—a few patents that fundamentally reshape their fields—from those with broader, more incremental advances. Examining both typical patterns and exceptional outliers across novelty, disruptiveness, and generality reveals where breakthrough innovations are concentrated and where incremental advancements prevail (see Tables 6 through 11; Figs. 3 and 4).

5. Discussion

This section discusses key findings (Section 5.1), then addresses the implications for the Twin Transition (Section 5.2), followed by limitations (Section 5.3) and future research (Section 5.4). One cautionary note: given that our dataset was developed using USPTO patent data, conclusions pertaining to the directionality of AI-environmental technologies should be understood as applying specifically to the U.S. innovation ecosystem.

[3] For semantic embedding, we used the all-MiniLM-L6-v2 transformer, generating 384-dimensional vectors to capture contextual differences between patents (Vergou et al., 2023; Xiang et al., 2017). Embedding was fast, processing the full training set in about 9 s (2.04 iterations/second over 19 batches). The classifier was a three-layer neural network (384–128 to 64) with ReLU activations and dropout to prevent overfitting trained on an 80/20 split using the Adam optimizer (learning rate = 0.03) over 60 epochs. Batch sizes were tuned per phase: 32 for embedding, 16 for training, and 64 for prediction.

[4] https://github.com/kherman-cmd/AI-ENVI.

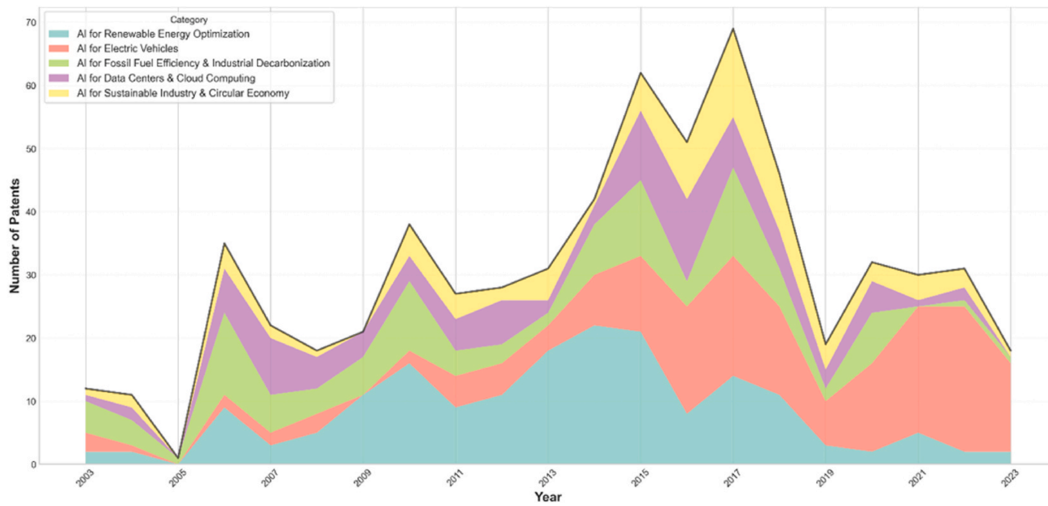

Fig. 1. Top 5 AI-ENVI categories (2003–2023).

Table 3
Descriptive statistics for high-value patent citations. Analysis based on top 1000 patents ranked by forward citation counts.

	Mean	Min	Max	Std.
Forward citation count	49.35	15	1171	98.76
Citation span (years)	9.64	1	24	4.10
Recency ratio	0.82	0	1	0.25

Table 4
Categorical forward patent citations, main categories.

Main category	Patent count	Percent
Renewable Energy Optimization	176	17.6
Electric Vehicles	175	17.5
Fossil Fuel Efficiency & Industrial Decarbonization	115	11.5
Data Centers & Cloud Computing	98	9.8
Circular Economy	80	8
Energy Storage	62	6.2
Environmental Monitoring	59	5.9
EV Charging Infrastructure	53	5.3
Internet of Things	48	4.8
Energy Grid Optimization	34	3.4
Smart Cities	32	3.2
Water Resource Management	31	3.1
Peer-to-Peer Energy Trading	16	1.6
Disaster Response & Resilience	11	1.1
Agriculture & Land Use	6	0.6
Climate & Weather Prediction	4	0.4

5.1. Key findings

Our semantic patent analysis shows that high-impact AI-environmental innovations are concentrated in a few domains: Renewable Energy Optimization (17.6 %), Electric Vehicles (17.5 %), and Fossil Fuel Efficiency & Industrial Decarbonization (11.5 %). Together, these account for 47 % of the top 1000 patents. Additional clusters include Data Centers & Cloud Computing (9.8 %), Circular Economy (8 %), Energy Storage (6.2 %), Environmental Monitoring (5.9 %), EV Charging Infrastructure (5.3 %), Internet of Things (4.8 %), and Energy Grid Optimization (3.4 %).

The static picture discussed above (Table 4), however, masks a much different story when viewed over time, particularly in recent years. As shown in Section 4.2 and Fig. 1, although AI for Fossil Fuel Efficiency & Industrial Decarbonization account for 11.5 % of top patents, this mainly reflects activity prior to 2018. The temporal dynamics show a fundamental shift after 2018, when this category largely disappears from high-impact innovation. Since 2020, AI for Electric Vehicles emerges as the dominant category, comprising the majority of influential patents even as overall volumes have declined from the 2017–2018 peak. Meanwhile, AI for Renewable Energy Optimization greatly diminishes following a peak in 2013, perhaps indicating the maturation of solar and wind energy technologies. Data Centers & Cloud Computing

Table 5
Subcategory top and total patents. Note: Showing subcategories with more than 20 patents. The full table is supplied in the Appendix Table 5.

Sub-category (main category)	Patent count	Percent
Autonomous EV Optimization (AI for Electric Vehicles)	69	6.9
Electric Planes and Drones (AI for Electric Vehicles)	68	6.8
Solar & Wind Energy Production (AI for Renewable Energy Optimization)	60	6
AI-Optimized Server Management (AI for Data Centers & Cloud Computing)	58	5.8
Air & Water Quality Analysis (AI for Environmental Monitoring & Compliance)	58	5.8
Green Manufacturing (AI for Sustainable Industry & Circular Economy)	47	4.7
Cloud Computing Energy Efficiency (AI for Data Centers & Cloud Computing)	37	3.7
Smart Grid Integration for EVs (AI for EV Charging Infrastructure)	36	3.6
Battery Health Prediction (AI for Energy Storage)	35	3.5
Chemical Process Optimization (AI for Fossil Fuel Efficiency & Industrial Decarbonization)	35	3.5
Smart Device Energy Consumption (AI for Internet of Things & Smart Devices)	32	3.2
Smart Grid & Energy Storage (AI for Renewable Energy Optimization)	32	3.2
Solar & Wind Forecasting (AI for Renewable Energy Optimization)	32	3.2
Dynamic Grid Management (AI for Energy Grid Optimization)	28	2.8
Hydrogen Fuel Cell Integration (AI for Energy Storage)	27	2.7
Hydrogen Technologies (AI for Renewable Energy Optimization)	26	2.6
Building Energy Management (AI for Smart Cities & Energy Efficiency)	24	2.4
Marine Ecosystem Monitoring (AI for Ocean & Water Resource Management)	24	2.4
Gas & Oil Extraction Efficiency (AI for Fossil Fuel Efficiency & Industrial Decarbonization)	23	2.3
Charging Infrastructure Prediction (AI for Electric Vehicles)	21	2.1
Geothermal Energy Optimization (AI for Renewable Energy Optimization)	21	2.1

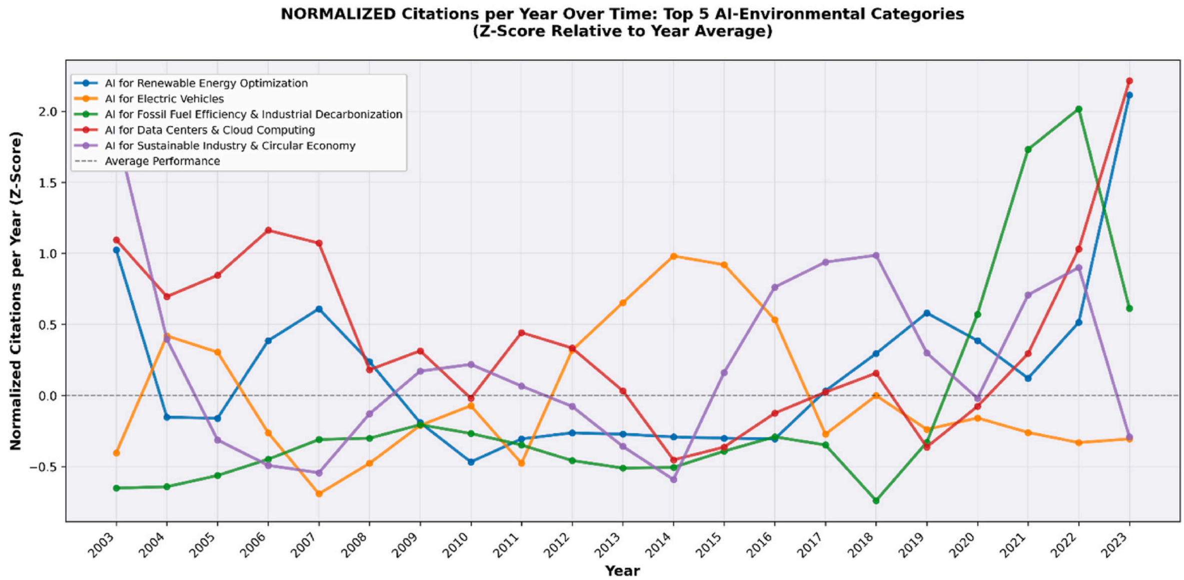

Fig. 2. Normalized citations for top five categories, based on forward citations.

Table 6
Top five novel patent categories.

Category	Novelty
1. AI for Ocean & Water Resource Management	0.945
2. AI for Agriculture & Land Use	0.941
3. AI for Environmental Monitoring & Compliance	0.93
4. AI for Energy Storage	0.909
5. AI for Smart Cities & Energy Efficiency	0.882

applications show more modest but consistent activity, while Sustainable Industry & Circular Economy innovations surge around 2017 before tapering off.

Drilling into subcategories adds nuance to these findings (Table 5). EV-related work dominates at the frontier—Autonomous EV Optimization (6.9 %), Electric Drones (6.8 %), and Smart-Grid Integration for EVs (3.6 %)—which together account for 17.3 % of all subcategories in the top 1000 patents. Data-center Efficiency appears in two complementary tracks—AI-Optimized Server Management (5.8 %) and Cloud Computing Energy Efficiency (3.7 %)—underscoring the role of software in operational gains. Renewable energy technologies are oriented toward supply optimization via Solar & Wind Energy Production (6 %), system coupling (Smart Grid & Storage, 3.2 %) and Solar & Wind Forecasting (3.2 %), complemented by energy storage via Battery-Health Prediction (3.5 %) and Hydrogen Fuel-cell Integration (2.7 %). Climate monitoring spans compliance-oriented Air & Water Quality Analysis (5.8 %) and Marine Ecosystems Monitoring (2.4 %). Fossil-Fuel Efficiency and Industrial Decarbonization remains present through Chemical-Process Optimization (3.5 %) and Gas & Oil Extraction Efficiency (2.3 %), suggesting targeted efficiency gains alongside broader electrification.

The metrics of novelty, disruptiveness, and generality reveal distinct technological frontiers as AI-environment patents move from invention to innovation (Tables 6–11; Figs. 2–4). At the category level, novelty is highest in Ocean & Water Resource Management (0.945), Agriculture & Land Use (0.941), Environmental Monitoring & Compliance (0.930), Energy Storage (0.909), and Smart Cities & Energy Efficiency (0.882). Disruptiveness peaks in Peer-to-Peer Energy Trading (0.447), EV Charging Infrastructure (0.342), and Disaster Response & Resilience (0.317), followed by Sustainable Industry & Circular Economy (0.288) and Environmental Monitoring & Compliance (0.266). Generality—-cross-domain reach—is led by EV Charging Infrastructure (0.962), Peer-to-Peer Energy Trading (0.821), Data Centers & Cloud Computing (0.713), Fossil Fuel Efficiency & Industrial Decarbonization (0.694), and Disaster Response & Resilience (0.693).

At the subcategory level, novelty concentrates in Grid-Level Storage Optimization (0.947), Weather Forecasting (0.945), Hydrogen Technologies (0.930), Tidal & Wave Energy (0.929), and Biogas & Biofuels (0.927). Disruptiveness is highest for Blockchain-Based Energy Trading (0.377), Disaster Impact Assessment (0.355), Electric Planes & Drones (0.343), Carbon Capture & Storage (0.325), and Geothermal Energy Optimization (0.306). Generality scores are highest in Blockchain-Based Energy Trading (0.824), Energy Demand Forecasting (0.815), Precision Agriculture (0.810), Disaster Impact Assessment (0.800), and Carbon Capture & Storage (0.798). Together, the three metrics surface different leaders at each level, highlighting parallel pathways from invention to innovation: novel niches, disruptive challengers, and broadly generalizable platforms.

Table 7
Top five novel patent subcategories.

Subcategory	Novelty
1. Grid-Level Storage Optimization	0.947
2. Weather Forecasting	0.945
3. Hydrogen Technologies	0.93
4. Tidal & Wave Energy	0.929
5. Biogas & Biofuels	0.927

5.2. *Quantitative assessment of the Twin Transition*

The promise of the Twin Transition is that digital and ETs will reinforce one another to drive systemic transformation. Our analysis of the 1000 most-cited AI–environmental patents suggests that, rather than seamless synergy, there is a rather fragmented and path-dependent convergence in which AI acts primarily as a performance amplifier within established technological systems. Forward citation patterns, indeed, confirm consolidation around mature technological fields.

Analysis across novelty, disruptiveness, and generality reveals important divergences from citation patterns, however. The most influential categories with respect to forward citations (renewables, EVs, fossil fuel optimization) rank considerably lower on novelty and disruptiveness.

These metrics reveal a striking disconnect between technological influence and innovation frontiers. The most cited categories rank

Table 8
Top five disruptive patent categories.

Category	Disruptiveness
1. AI for Peer-to-Peer Energy Trading	0.447
2. AI for EV Charging Infrastructure	0.342
3. AI for Disaster Response & Resilience	0.317
4. AI for Sustainable Industry & Circular Economy	0.288
5. AI for Environmental Monitoring & Compliance	0.266

Table 9
Top five disruptive patent subcategories.

Subcategory	Disruptiveness
1. Blockchain-Based Energy Trading	0.377
2. Disaster Impact Assessment	0.355
3. Electric Planes and Drones	0.343
4. Carbon Capture & Storage	0.325
5. Geothermal Energy Optimization	0.306

Table 10
Top five categories for patent generality.

Category	Generality
1. AI for EV Charging Infrastructure	0.962
2. AI for Peer-to-Peer Energy Trading	0.821
3. AI for Data Centers & Cloud Computing	0.713
4. AI for Fossil Fuel Efficiency & Industrial Decarbonization	0.694
5. AI for Disaster Response & Resilience	0.693

Table 11
Top five subcategories for patent generality.

Subcategory	Generality
1. Blockchain-Based Energy Trading	0.824
2. Energy Demand Forecasting	0.815
3. Precision Agriculture	0.81
4. Disaster Impact Assessment	0.8
5. Carbon Capture & Storage	0.798

considerably lower on novelty and disruptiveness. Instead, novelty concentrates in emerging niches: Ocean & Water Resource Management, Environmental Monitoring & Compliance, and Energy Storage (Table 6); and, at the subcategory leve, Grid-Level Storage Optimization and Weather Forecasting (Table 7). Disruptiveness centers on structural energy system innovations. Peer-to-Peer Energy Trading and EV Charging Infrastructure dominate category rankings (Table 8), while Blockchain-Based Energy Trading and Disaster Impact assessment lead subcategories (Table 9). Notably, these disruptive domains also exhibit exceptional generality: EV Charging Infrastructure shows the highest cross-domain applicability (0.962), followed by Peer-to-Peer Energy Trading (Table 10). At the subcategory level, for generality, Blockchain-Based Trading (0.824) and Energy Demand Forecasting (0.815) demonstrate remarkable versatility across fields (Table 11). This overlap between disruption and generality suggests these technologies possess both transformative depth and broad diffusion potential (Appio et al., 2024).

Though these findings are not inherently negative, they do suggest that transformative innovation at the AI–ET nexus may take longer to materialize, and be more diffuse, than often anticipated. Concrete examples from the literature illustrate this incremental orientation. Memari et al. find that AI is primarily applied to grid flexibility, predictive maintenance of solar and wind assets, and advanced energy forecasting (Memari et al., 2024). In the EV sector, applications focus on adaptive charging, vehicle-to-grid integration, and battery diagnostics (Hasan et al., 2021; Xin et al., 2023). Consistent with prior research, we also find that high-impact patents concentrate in Clean Energy Integration (Andoni et al., 2019; Nair et al., 2024). These optimization applications—predictive maintenance, adaptive charging, forecasting—exemplify performance amplification within existing systems rather than systemic transformation. Disruptive innovations cluster instead in market-restructuring domains (Tables 8–9), confirming that truly transformative AI-ET convergence remains niche rather than pervasive.

Such findings, moreover, reflect the sentiment of Kus and Jackson who emphasize that the direction of governance matters: policy and institutional choices determine whether diffusion of new technologies disrupts incumbents by enabling substitution, or is absorbed into existing regimes in ways that reinforce them (Kus & Jackson, 2025). One impending result, however, could be that the innovation landscape becomes dominated by incremental improvements (Cicerone et al., 2023; Faggian et al., 2025; Montresor and Vezzani, 2023). Importantly for this work, in the absence of strategic redirection, the wide adoption of digital tools such as AI may entrench unsustainable industrial pathways (European Commission, 2022).

Subcategories with high novelty and disruptiveness—Electricity Grid Storage Optimization, Blockchain-based Energy Trading, Weather Forecasting—cluster in smaller, less mature niches. Carbon Capture & Storage (CCS) also ranks among the most disruptive areas (Table 9), but its potential is contested: while positioned as a transitional decarbonization technology, CCS is often linked to enhanced oil recovery and other fossil fuel applications (Herman et al., 2024; Herman, Sovacool, et al., 2025). This risks reinforcing carbon lock-in, where efficiency gains extend the lifespan of high-emission infrastructures rather than displacing them (Herman, Hall, et al., 2025; Tan & Chen, 2025). Consequently, AI risks becoming a tool for optimizing rather than transforming carbon-intensive systems. CCS may prove essential for hard-to-abate sectors like cement and steel and for negative emissions through direct air capture (Sovacool et al., 2024), but whether its disruptive potential accelerates or delays deep decarbonization remains an open question.

Our findings suggest that AI deployment bifurcates along two markedly different pathways. In the EV domain, it drives sustainability-oriented improvements like vehicle-to-grid integration that accelerate low-carbon mobility (Hasan et al., 2021; Xin et al., 2023). By contrast, across fossil-fuel value chains and industry, AI predominantly enhances efficiency that reduces operating costs while extending the profitability and longevity of high-emission assets (Tan & Chen, 2025). Importantly, these efficiency gains may postpone substitution toward low-carbon technologies (Ochieng et al., 2024). Evidence from refinery optimization and methane detection underscores similar dynamics—referred to as "greenwashing by optimization" (Maslej et al., 2025)—where efficiency improvements sustain carbon-intensive infrastructures without delivering meaningful emission reductions (Hussain et al., 2024; Nadim et al., 2023).

Generality metrics reinforce this concern: Fossil-Fuel Optimization & Industrial Decarbonization patents diffuse broadly across technological domains, signaling wide adoption. Absent strong policy direction, these dynamics risk delaying low-carbon substitution by keeping fossil infrastructure economically attractive. Policymakers should therefore balance innovation efforts to ensure that high-emitting fuels and industries are gradually sunset rather than indefinitely prolonged as a result of technological advancement (Verrier & Strachan, 2024).

These patterns align with prior research showing digital–environmental convergence reinforcing rather than transforming incumbent systems (Igna & Venturini, 2023). Our novelty and disruptiveness metrics confirm this: the most influential categories score relatively low, indicating consolidation rather than frontier experimentation. Governance proves decisive. Without policy coordination, digitalization entrenches incumbent power (Sareen & Haarstad, 2021), emissions rise despite efficiency gains (Bianchini et al., 2023), and AI's energy demands amplify consumption (Luers et al., 2024).

As AI becomes general-purpose, it may more easily embed into existing systems rather than autonomously driving transformation

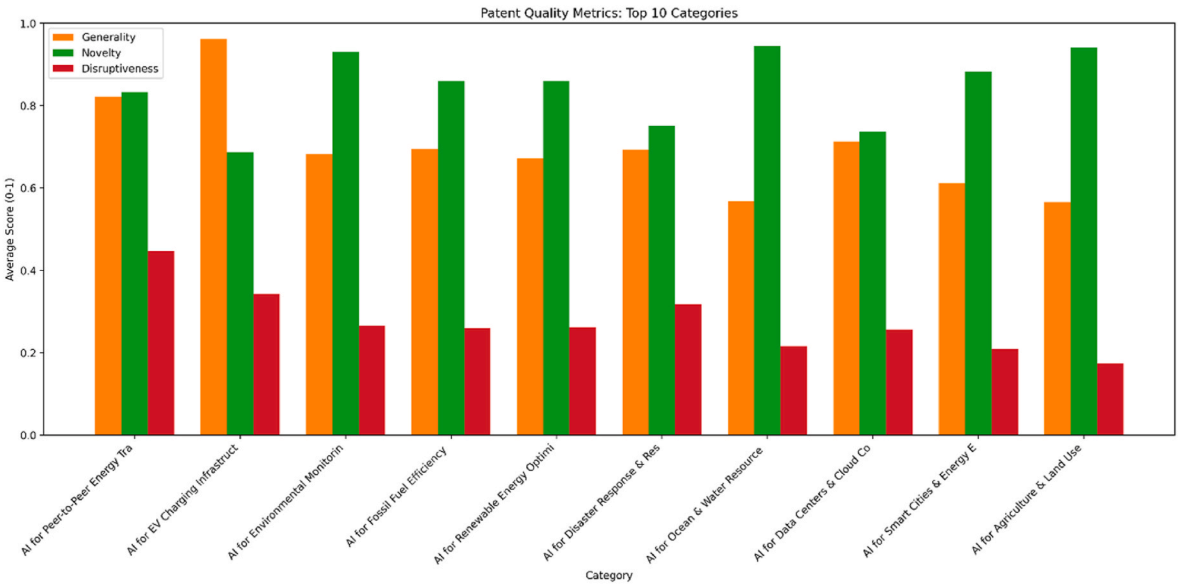

Fig. 3. Overall patent quality metrics, top ten categories.

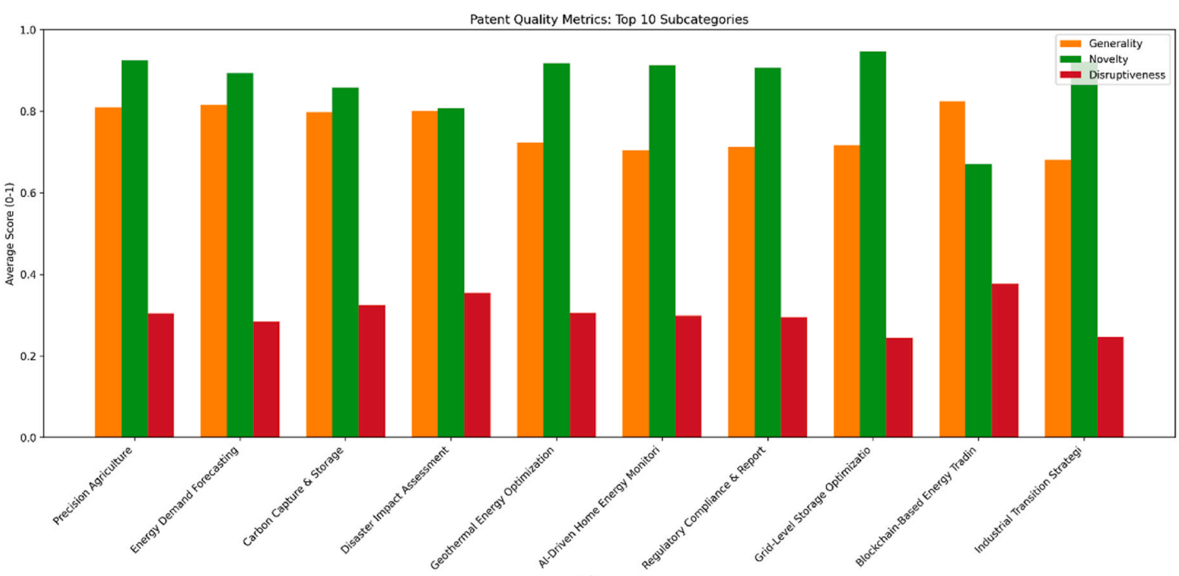

Fig. 4. Overall patent quality metrics, top ten subcategories.

(Crafts, 2021; Gibney, 2022). Realizing its green potential requires aligning digital innovation with decarbonization objectives (Rehman et al., 2023). Our metrics draw attention to experimental niches with breakthrough potential—hydrogen, storage optimization, blockchain-based energy systems—where targeted policy can reorient innovation pathways (Lin & Sovacool, 2020; Lopolito et al., 2022). On the other hand CCS, which demonstrates both disruptive potential and carbon lock-in risks, deserves particular attention. The core task is steering digitalization toward structural transformation rather than reinforcing incumbent fossil systems. Without targeted governance, AI will consolidate carbon-intensive pathways; with foresight, it could accelerate low-carbon transitions while enabling managed phase-outs where necessary.

5.3. Limitations

Though this study provides new empirical insights into the intersection of AI and ETs, there are several important limitations and caveats to consider. First, patent data, while widely used in innovation studies, are imperfect indicators of real technological deployment (Laplume et al., 2014). Many ET and AI applications are underrepresented. This is true in particular for open-source software and service-oriented innovations, especially as they tend not to rely on formal intellectual property systems (Andersen et al., 2025).

Second, our dataset is based on USPTO filings, which introduces jurisdictional bias. The dominance of U.S.-based assignees (roughly 70 % of AI patents) likely obscures innovation trajectories that are significant in China and the Global South (Habibollahi Najaf Abadi & Pecht, 2020).

Third, forward citations are an imperfect measure of technological significance or innovation. High citation counts may reflect strategic patenting, legal defensibility, or alignment with dominant paradigms rather than genuine novelty or transformative potential (Marx & Fuegi, 2020; Squicciarini et al., 2013). In practice, the most cited patents are often associated with mature, efficiency-enhancing technologies rather than disruptive breakthroughs.

Fourth, while we extend the analysis by incorporating novelty, disruptiveness, and generality, these measures also have limitations. Novelty depends on diversity in backward citations, which may privilege patents that borrow widely rather than those introducing fundamentally new ideas. Disruptiveness captures shifts in subsequent citation patterns but may misinterpret incremental advances in new citation clusters as "disruption." Generality measures diffusion across technological classes, yet high scores may signal broad applicability without necessarily reflecting environmental benefit. These metrics are, in addition, calculated only within our AI-ENVI dataset and are not benchmarked against the broader USPTO patent universe, limiting comparative insights.

Fifth, our machine learning classification enables pattern detection at scale but may misclassify inventions that deviate from conventional categories (J.-S. Lee & Hsiang, 2020; Yu et al., 2024a). Exclusion of pre-grant patents and unpatented knowledge flows further limits coverage, particularly for academic research, start-ups, and Global South innovation ecosystems (Levine & Sichelman, 2018; W. Liu, Tao, & Bi, 2022).

Finally, our analysis provides a retrospective view limited to patents through 2023. This period captures AI focused on prediction, optimization, and pattern recognition, but predates the emergence of generative AI models. Our dataset therefore cannot capture the full impact of these general-purpose AI systems, which are already reshaping materials design, environmental monitoring, and other ET domains. The post-2023 wave of LLMs and related AI breakthroughs will likely transform the AI–ET nexus in radical ways only partially visible in current patent data (Andersen et al., 2025; Pelaez et al., 2024).

In sum, while our approach provides a systematic lens on codified technological trends, it may nevertheless undercount distributed, early-stage, or socially embedded innovations. And while the patent-based indicators we have computed (including novelty, disruptiveness, and generality) are able to capture some elements of the Twin Transition, much more work is to be done, as discussed in the final part of Section 5.

5.4. Future research directions

This study offers a systematic assessment of AI–environmental technology linkages through patents, but several gaps remain for future work. Patent data can expose technological trajectories, yet this is not necessarily indicative of material innovations. While our analysis shows where AI and ETs are converging from an intellectual property perspective, this does not imply that tangible products or innovations have become commercially successful.

Linking patents with firm-level emissions data, scientific publications, and AI investment flows would shed more light on the potential impact of the ET-AI convergence on climate change mitigation and the energy transition (Marx & Fuegi, 2020). The geographical scope of analysis could also be expanded. Our dataset draws on USPTO filings, which risks underrepresenting non-Western regions. Though U.S. entities account for about 70 % of global AI patents (Habibollahi Najaf Abadi & Pecht, 2020), China's technological rise certainly merits research attention (Zu et al., 2025). Incorporating EPO, WIPO, and national filings would enable more inclusive comparisons of AI–environmental trajectories.

Classification systems likewise warrant scrutiny. Standard taxonomies such as the IPC are rigid and difficult to leverage for deeper reclassifcation. In addition, our supervised classification methodology may have overlooked unconventional innovations, particularly high-value patent domains. Advances in text-as-data and NLP offer promising tools: semantic models can refine green patent identification, while hybrid approaches combining embeddings with metadata could generate more adaptive taxonomies (Garrido-Merchán et al., 2023).

Patent metrics themselves require refinement. Forward citations may reflect incumbent strategies or defensibility rather than disruptive impact. Complementary measures such as novelty, generality, and disruptiveness indeed can add nuance but also have limitations (Biggi et al., 2025). High novelty may reflect recombination, while high generality can signal diffusion without environmental benefit; patents that appear original and general do not always translate into adoption or systemic change. Future research must therefore interrogate the relationship between patent indicators, governance structures, and real-world decarbonization outcomes, moving beyond proxies to assess how AI–ET convergence reshapes innovation pathways in practice.

Finally, determining the net climate impact of AI-ET convergence demands more granular assessment. As already noted, making fossil fuel and industrial decarbonization more efficient is not inherently bad. What matters is whether such efficiency enables the sunsetting of climate-negative industries and technologies or extends their lifespan. Future research should therefore examine these dynamics to inform targeted policy interventions.

6. Conclusion

This article examined the extent to which artificial intelligence (AI) and environmental technologies (ETs) are converging, using a novel dataset of nearly 8000 AI–ENVI patents filed from 2003 to 2023. Our analysis demonstrated that convergence is real but uneven. Based on forward citations, three domains dominate: AI for Renewable Energy Optimization, Electric Vehicles, and Fossil Fuel Efficiency. This concentration reflects the maturity of these sectors and highlights AI's role as a performance amplifier within established technological systems rather than as a driver of radical disruption. That a large share of highly cited patents focus on fossil fuel extraction, refining, and process optimization as well as broader industrial decarbonization—and also that this category scores high on generality—underscores how AI can inadvertently reinforce incumbent systems, potentially delaying substitution towards low-carbon alternatives. Unless policy actively steers innovation toward sustainable and/or transformative ends, the risk of carbon lock-in remains pronounced.

Novelty, generality, and disruptive metrics paint a more nuanced picture, however. While citation influence is concentrated in mature domains, smaller technological classes such as Energy Storage Optimization and Blockchain-based Energy Trading are beginning to become more disruptive. High generality scores for domains like EV Charging suggest broader spillover potential. Whether this diffusion challenges incumbent energy technologies or becomes absorbed by them depends on governance structures and policy direction. Furthermore, we note that we did not directly assess incumbent companies here, but rather incumbent technologies; future research could probe further into industry and firm-specific technological trajectories. In addition, from a policy perspective, regional asymmetries in infrastructure and absorptive capacity strongly condition innovation trajectories. Without supportive institutions, AI adoption risks deepening technological inequalities, and inadvertently exacerbating climatic and environmental issues.

Understanding and ultimately steering AI's growing role within the Twin Transition demands deeper insight into how these technological domains are converging, diverging, or spawning novel fields. The transformative potential of this transition will likely hinge less on technological capacity than on the governance frameworks, institutional arrangements, and incentive structures that channel innovation toward low-carbon pathways. Yet a fundamental question remains: will such governance initiatives steer the Twin Transition toward genuine sustainability, or will they entrench unsustainable trajectories under a green veneer?

CRediT authorship contribution statement

Kyle S. Herman: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tatiana Gaitan Amortegui:** Writing – original draft, Visualization, Investigation, Formal analysis. **Steve Griffiths:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix I. Classification

The research team employed Anthropic's Claude Sonnet 4 to support the development of a comprehensive and hierarchically structured categorization framework. This framework was built through a multi-stage process integrating authoritative sources and expert validation:

1. Academic Literature Integration: Foundational insights were drawn from leading studies on AI applications in climate and environmental domains, including: Cowls et al. (2023), Kaack et al. (2022), Rolnick et al. (2022) Dauvergne (2022), Marín-Vinuesa et al. (2020).
2. Patent Classification Systems Analysis: Claude analyzed multiple official patent classification systems to inform category design:
   a. USPTO Artificial Intelligence Patent Dataset (AIPD, 2020)
   b. WIPO Technology Trends 2019: Artificial Intelligence
   c. EPO: Patents and the Fourth Industrial Revolution (2021)
   d. EPO Y02/Y04S Climate Change Mitigation Classifications
   e. WIPO IPC Green Inventory EU Taxonomy for Sustainable Activities
3. Technical Standards Incorporation: Classifications from leading standards bodies were integrated to ensure alignment with international technical guidance:
   a. ISO/IEC JTC 1/SC 42 (AI standards)
   b. IEEE Sustainable AI Working Group
   c. IEA (2021): Digitalization and Energy
   d. UNEP (2020): Data-Driven Environmental Monitoring Framework
4. Emerging Technology Trends Analysis: Recent trends were analyzed using patent filings, conference proceedings, and industry reports. This enabled the identification of nascent AI–environmental subdomains underrepresented in established systems.
5. Domain Expert Validation: Three domain experts with backgrounds in environmental technology and AI innovation independently labeled a subset of 600 patents and reviewed the draft classification system to refine category boundaries, identify omissions, and validate definitions. Inter-annotator agreement on the manual labeling was measured using Cohen's kappa ($k = 0.82$), indicating strong consistency across reviewers in assigning patents to categories.
6. We built a high-performance classification pipeline using Python, leveraging tools such as scikit-learn, PyTorch, and SentenceTransformer.
7. Hierarchical Organization: Claude supported the hierarchical structuring of the taxonomy, organizing broad AI–environmental intersections into granular subcategories to allow for flexible classification at multiple levels of specificity. Classification Performance Validation: The trained classifier was evaluated through k-fold cross-validation (k = 5) on the manually labeled dataset of 600 patents, demonstrating robust performance across multiple validation splits:
   a. Overall classification accuracy: 87.3 %
   b. Macro-averaged F1-score: 0.84
   c. Precision: 0.86 (macro-averaged)
   d. Recall: 0.83 (macro-averaged)
   e. Category-specific performance ranged from F1 = 0.76 (Cloud Computing Energy Efficiency) to F1 = 0.94 (Solar and Wind Forecasting).
8. Test Set Performance: A held-out test set of 120 patents (20 % of labeled data) achieved: Accuracy: 85.8 % F1-score: 0.82 Classification confidence scores averaged 0.78 across all predictions.
9. Alignment with Sustainability Frameworks Final adjustments ensured alignment with key sustainability benchmarks, including the UN Sustainable Development Goals (SDGs) and the IPCC's mitigation/adaptation categories.

Appendix II. LLM keyword dictionary

Below is the dictionary used for re-classification based on the steps from Appendix I.

Dictionary used for re-classification

Category	Subcategory	Example Applications
AI for Renewable Energy Optimization	Solar & Wind Energy Production	Solar panel output optimization, wind farm layout optimization, generation efficiency improvement
	Solar & Wind Forecasting	Solar power generation prediction, wind energy output forecasting, renewable resource assessment
	Hydropower & Marine Energy	Hydropower optimization, tidal energy forecasting, wave energy prediction
	Geothermal Energy Optimization	Geothermal reservoir modeling, thermal energy storage, drilling optimization
	Smart Grid & Energy Storage	Intelligent load balancing, virtual power plant coordination, battery management systems
	Renewable Resource Assessment	Renewable energy potential mapping, resource availability forecasting
	Biogas & Biofuels	Biogas production optimization, biofuel yield prediction, feedstock selection
	Tidal & Wave Energy	Tidal energy site selection, wave height prediction, energy conversion efficiency
AI for Climate & Weather Prediction	Extreme Weather Forecasting	Hurricane trajectory modeling, flood prediction systems, wildfire risk assessment

(continued on next page)

(*continued*)

Category	Subcategory	Example Applications
	Long-Term Climate Modeling	Multi-model climate ensembles, downscaling techniques, climate scenario modeling
	Neural Networks for Climate Risk	Infrastructure vulnerability predictions, financial risk modeling, business continuity planning
AI for Environmental Monitoring & Compliance	Air & Water Quality Analysis	Air pollution forecasting, groundwater contamination detection, water quality monitoring
	Biodiversity & Ecosystem Health	Species identification, habitat classification, coral reef health assessment
	Regulatory Compliance & Reporting	Emissions monitoring automation, climate disclosure processing, ESG impact analysis
AI for Sustainable Industry & Circular Economy	Green Manufacturing	Energy-efficient production scheduling, predictive maintenance, waste heat recovery
	Supply Chain Optimization	Sustainable sourcing, low-carbon logistics, circular economy tracking
	Material Discovery & Recycling	Biodegradable polymer design, recyclable material identification, remanufacturing optimization
AI for Smart Cities & Energy Efficiency	Building Energy Management	Intelligent HVAC control, occupancy-based optimization, smart lighting systems
	Infrastructure & Transportation	Traffic flow efficiency, public transit optimization, low-emission route planning
	Climate-Adaptive Architecture	Weather-responsive facades, natural ventilation optimization, urban heat mitigation
AI for Fossil Fuel Efficiency & Industrial Decarbonization	Carbon Capture & Storage	Sequestration site selection, soil carbon measurement, carbon sink enhancement
	Methane Detection & Reduction	Leak detection using satellite data, fugitive emissions monitoring, methane mitigation planning
	Refinery Operations	Production yield optimization, flaring reduction, energy intensity monitoring
	Hydrogen Technologies	Hydrogen production efficiency, storage optimization, fuel cell performance
	Clean Energy Integration	Grid integration of renewables with industrial processes, hybrid energy system optimization
	Gas & Oil Extraction Efficiency	Enhanced oil recovery optimization, drilling emissions reduction, reservoir management
	Chemical Process Optimization	Ammonia production efficiency, ethylene cracking optimization, process integration modeling
	Heavy Industry Decarbonization	Cement clinker reduction, steel furnace optimization, aluminum smelting efficiency
	Fossil Fuel Energy Efficiency	Industrial heat recovery, carbon capture material screening, process emissions reduction
	Industrial Transition Strategies	Predictive emissions modeling, energy transition pathways, low-carbon retrofitting
AI for Agriculture & Land Use	Precision Agriculture	Crop yield prediction, precision irrigation, automated harvesting
	Deforestation & Land Use Monitoring	Deforestation detection, soil carbon tracking, invasive species monitoring
	Climate-Resilient Farming	Pest detection, hyperspectral imaging analysis, drought adaptation strategies
AI for Disaster Response & Resilience	Disaster Impact Assessment	Post-disaster damage assessment, emergency resource allocation, resilient infrastructure planning
	Disaster Recovery & Adaptation	Recovery planning optimization, adaptation policy modeling, resilience enhancement
	Microgrid Control & Islanded Systems	Energy market participation, multi-resource coordination, grid resilience modeling
AI for Ocean & Water Resource Management	Marine Ecosystem Monitoring	Ocean acidification tracking, fish stock prediction, marine biodiversity modeling
	Coastal & Offshore Energy Systems	Offshore wind forecasting, coastal erosion monitoring, tidal power optimization
	Water Resource Optimization	Watershed modeling, leak detection, smart irrigation systems
AI for Environmental Policy & Decision Support	NLP for Climate Policy	Climate regulation analysis, ESG report processing, sustainability impact assessment
	AI for Investment & Green Finance	Sustainable investment screening, policy risk evaluation, financial impact modeling
	Urban & Regional Planning	Energy-efficient zoning, land-use change forecasting, scenario-based urban planning
AI for Electric Vehicles	EV Battery Management	Battery degradation prediction, energy density improvement, thermal management
	Autonomous EV Optimization	AI-driven route planning for EVs, smart vehicle charging schedules
	Electric Planes and Drones	Electric aircraft range optimization, drone delivery efficiency, aerial mobility
	Charging Infrastructure Prediction	Infrastructure planning, demand forecasting, real-time charging station analysis
AI for Energy Storage	Grid-Level Storage Optimization	Grid-scale battery deployment strategies, AI-optimized dispatching, storage resilience
	Battery Health Prediction	Predicting battery lifespan, optimizing charging cycles, failure prevention
	Hydrogen Fuel Cell Integration	Hydrogen energy carrier optimization, fuel cell system control, efficiency modeling
AI for Energy Grid Optimization	Dynamic Grid Management	Demand-response coordination, blackout prevention, peak load management
	Power Outage Prediction	AI-driven grid maintenance, outage detection, smart recovery
	Energy Demand Forecasting	Predictive analytics for power usage, energy cost minimization, grid balancing
AI for Data Centers & Cloud Computing	Data Center Cooling Optimization	Liquid cooling optimization, AI-based workload management, renewable integration
	Cloud Computing Energy Efficiency	Server energy efficiency improvements, carbon footprint reduction in cloud data centers
	Renewable Energy & Energy Storage	Datacenter renewable integration, battery storage optimization, energy arbitrage
	AI-Optimized Server Management	AI-powered data center automation, workload distribution efficiency
AI for Internet of Things & Smart Devices	Smart Device Energy Consumption	Household electricity use prediction, smart meter analytics, demand-side response
	AI-Driven Home Energy Monitoring	Energy monitoring for homes, appliances, and IoT ecosystems
	IoT-Based Grid Interaction	Real-time smart grid communication, IoT-enabled energy tracking, adaptive load shifting
AI for EV Charging Infrastructure	Fast Charging Optimization	Fast charging scheduling, grid impact modeling, charger deployment planning
	Charging Network Expansion	Optimization of public EV charging networks, station expansion strategies
	Smart Grid Integration for EVs	Vehicle-to-grid (V2G) systems, smart EV-grid energy transactions
AI for Peer-to-Peer Energy Trading	Blockchain-Based Energy Trading	AI-driven peer-to-peer energy trading models, blockchain-secured exchanges
	Decentralized Energy Markets	Decentralized grid trading platforms, household energy market optimization
	Consumer Energy Trading Platforms	AI-based pricing models for localized energy markets, renewable energy exchange

Categorical forward patent citations, subcategories

Sub-category	Top patents (1k)	Percent	All patents	Percent
Autonomous EV Optimization	69	6.9	652	8.29
EV Drones	68	6.8	309	3.93
Solar & Wind Energy Production	60	6	469	5.96
AI-Optimized Server Management	58	5.8	382	4.86
Air & Water Quality Analysis	58	5.8	446	5.67
Green Manufacturing	47	4.7	438	5.57
Cloud Computing Efficiency	37	3.7	301	3.83
Smart Grid Integration for EVs	36	3.6	206	2.62
Battery Health Prediction	35	3.5	268	3.41
Chemical Process Optimization	35	3.5	416	5.29
Smart Device Consumption	32	3.2	197	2.51
Smart Grid & Energy Storage	32	3.2	277	3.52
Solar & Wind Forecasting	32	3.2	281	3.57
Dynamic Grid Management	28	2.8	243	3.09
Hydrogen Fuel Cell Integration	27	2.7	375	4.77
Hydrogen Technologies	26	2.6	260	3.31
Building Energy Management	24	2.4	107	1.36
Marine Ecosystem Monitoring	24	2.4	97	1.23
Gas & Oil Extraction Efficiency	23	2.3	162	2.06
Charging Infrastructure Prediction	21	2.1	111	1.41
Geothermal Energy Optimization	21	2.1	114	1.45
Supply Chain Optimization	18	1.8	53	0.67
EV Battery Management	17	1.7	163	2.07
Fossil Fuel Energy Efficiency	17	1.7	195	2.48
Material Discovery & Recycling	15	1.5	167	2.12
IoT-Based Grid Interaction	13	1.3	75	0.95
Biogas & Biofuels	11	1.1	137	1.74
Heavy Industry Decarbonization	11	1.1	117	1.49
Charging Network Expansion	10	1	45	0.57
Microgrid Control Systems	10	1	44	0.56
Infrastructure & Transportation	8	0.8	38	0.48
Decentralized Energy Markets	7	0.7	19	0.24
Fast Charging Optimization	7	0.7	57	0.72
Renewable Resource Assessment	7	0.7	91	1.16
Water Resource Optimization	7	0.7	137	1.74
Blockchain-Based Energy Trading	5	0.5	22	0.28
Climate-Resilient Farming	5	0.5	58	0.74
Clean Energy Integration Grid	4	0.4	50	0.64
Consumer Energy Trading	4	0.4	18	0.23
Industrial Transition Strategies	4	0.4	50	0.64
AI-Driven Home Energy Monitoring	3	0.3	10	0.13
Carbon Capture & Storage	3	0.3	25	0.32
Energy Demand Forecasting	3	0.3	55	0.7
Power Outage Prediction	3	0.3	35	0.45
Refinery Operations	3	0.3	20	0.25
Tidal & Wave Energy	3	0.3	9	0.11
Weather Forecasting	3	0.3	17	0.22
Data Center Optimization	2	0.2	13	0.17
Methane Detection & Reduction	2	0.2	10	0.13
Regulatory Compliance	1	0.1	11	0.14
Grid-Level Storage Optimization	0	0	11	0.14
Total	1000		7863	

Appendix III. Novelty, disruptiveness, and generality

A. Novelty Calculation

Definition: Novelty measures the rarity of IPC class combinations within a given year, using rolling historical baselines.
Mathematical Formulation:
$Novelty\_i = 1/(1 + frequency\_ij \times \alpha)$
Where:
$frequency\_ij$ = frequency of IPC class j in year i
α = scaling parameter (set to 3.0)
Computational Steps:
For each year t, calculate IPC class frequencies:
$frequency\_jt = count(IPC\_j \text{ in } year\_t)/total\_patents\_in\_year\_t$
Apply inverse frequency transformation:
$Novelty\_it = 1/(1 + frequency\_jt \times 3.0)$
Clip values to [0,1] range for normalization.

B. Disruptiveness Calculation

Definition: Disruptiveness measures the extent to which follow-on work shifts attention away from cited predecessors, incorporating citation recency and temporal dynamics.

Mathematical Formulation:

Disruptiveness_i = (Recency_Ratio_i × ln(1 + Citations_i))/ln(1 + Patent_Age_i)/γ.

Where:

Recency_Ratio_i = proportion of citations received in recent years.

Citations_i = forward citation count (capped at 95th percentile)

Patent_Age_i = 2024 - filing_year_i

γ = scaling factor (set to 5.0)

Computational Steps:

Calculate patent age:

Patent_Age_i = current_year - filing_year_i.

Apply logarithmic transformation to handle citation skewness:

ln_citations = ln(1 + forward_citation_count_capped_i)

ln_age = ln(1 + Patent_Age_i)

Combine with recency weighting:

Disruptiveness_i = (recency_ratio_i × ln_citations)/ln_age/5.0.

Clip to [0,1] range.

C. Generality Calculation

Definition: Generality measures the breadth of influence across technological fields, incorporating both citation volume and temporal persistence.

Mathematical Formulation:

Generality_i = [ln(1 + Citations_i)/ln(1 + Max_Citations)] × (0.5 + 0.5 × Recency_Ratio_i)

Computational Steps:

Normalize citation counts logarithmically:

base_generality = ln(1 + citations_capped_i)/ln(1 + max_citations_in_dataset)

Apply recency adjustment:

recency_weight = 0.5 + 0.5 × recency_ratio_i.

Final generality score:

Generality_i = base_generality × recency_weight.

Clip to [0,1] range.

Outlier Handling:

Forward citation counts capped at 95th percentile to prevent extreme values from skewing calculations.

Missing values handled through listwise deletion.

Patent age calculated as of 2024 reference year.

Normalization:

All metrics scaled to [0,1] range for comparability.

Logarithmic transformations applied to citation counts to handle right-skewed distributions.

Quality Controls:

Patents with fewer than 3 years of potential citation window excluded from disruptiveness calculations.

IPC classification consistency verified across dataset.

Temporal coverage requirements: minimum 3 data points for trend analysis.

This methodology allows for reproducible calculation of patent quality dimensions that distinguish between different types of technological impact and innovation patterns within AI-environmental domains.

Data availability

Data will be made available on request.

References

Acemoglu, D. (2021). *Harms of AI*. National Bureau of Economic Research. https://doi.org/10.3386/w29247 (Working Paper No. 29247).

Adewoyin, M. A., Adediwin, O., & Audu, A. J. (2025). Artificial intelligence and sustainable energy development: A review of applications, challenges, and future directions. *International Journal of Multidisciplinary Research and Growth Evaluation, 6* (2), 196–203. https://doi.org/10.54660/.IJMRGE.2025.6.2.196-203

Agrawal, A. K., Gans, J., & Goldfarb, A. (2019). The economics of artificial intelligence: An agenda. https://doi.org/10.7208/chicago/9780226613475.001.0001.

Andersen, J. P., Degn, L., Fishberg, R., Graversen, E. K., Horbach, S. P. J. M., Schmidt, E. K., Schneider, J. W., & Sørensen, M. P. (2025). Generative artificial intelligence (GenAI) in the research process – A survey of researchers' practices and perceptions. *Technology in Society, 81*, Article 102813. https://doi.org/10.1016/j.techsoc.2025.102813

Andoni, M., Robu, V., Flynn, D., Abram, S., Geach, D., Jenkins, D., McCallum, P., & Peacock, A. (2019). Blockchain technology in the energy sector: A systematic review of challenges and opportunities. *Renewable and Sustainable Energy Reviews, 100*, 143–174. https://doi.org/10.1016/j.rser.2018.10.014

Appio, F. P., Platania, F., & Hernandez, C. T. (2024). Pairing AI and sustainability: Envisioning entrepreneurial initiatives for virtuous twin paths. *IEEE Transactions on Engineering Management, 71*, 11669–11686. https://doi.org/10.1109/TEM.2024.3428913

Archibugi, D., & Pietrobelli, C. (2003). The globalisation of technology and its implications for developing countries. *Technological Forecasting and Social Change, 70* (9), 861–883. https://doi.org/10.1016/S0040-1625(02)00409-2

Attia, P. M., Grover, A., Jin, N., Severson, K. A., Markov, T. M., Liao, Y.-H., Chen, M. H., Cheong, B., Perkins, N., Yang, Z., Herring, P. K., Aykol, M., Harris, S. J., Braatz, R. D., Ermon, S., & Chueh, W. C. (2020). Closed-loop optimization of fast-charging protocols for batteries with machine learning. *Nature, 578*(7795), 397–402. https://doi.org/10.1038/s41586-020-1994-5

Bekamiri, H., Hain, D. S., & Jurowetzki, R. (2024). PatentSBERTa: A deep NLP based hybrid model for patent distance and classification using augmented SBERT. *Technological Forecasting and Social Change, 206*, Article 123536. https://doi.org/10.1016/j.techfore.2024.123536

Bergman, E., Dürlich, L., Arthurson, V., Sundström, A., Larsson, M., Bhuiyan, S., Jakobsson, A., & Westman, G. (2023). BERT based natural language processing for triage of adverse drug reaction reports shows close to human-level performance. *PLOS Digital Health, 2*(12), Article e0000409. https://doi.org/10.1371/journal.pdig.0000409

Bianchini, S., Damioli, G., & Ghisetti, C. (2023). The environmental effects of the "twin" green and digital transition in European regions. *Environmental and Resource Economics, 84*(4), 877–918. https://doi.org/10.1007/s10640-022-00741-7

Biggi, G., Iori, M., Mazzei, J., & Mina, A. (2025). Green intelligence: The AI content of green technologies. *Eurasian Business Review*. https://doi.org/10.1007/s40821-024-00288-1

Brea, E. (2024). The yin yang of AI: Exploring how commercial and non-commercial orientations shape machine learning innovation. *Research Policy, 53*(6), Article 105008. https://doi.org/10.1016/j.respol.2024.105008

Brevini, B. (2023). Artificial intelligence, artificial solutions: Placing the climate emergency at the center of AI developments. In *Technology and sustainable development*. Routledge.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-Curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics, 13*(1), 333–372. https://doi.org/10.1257/mac.20180386

Byun, S. K., Oh, J.-M., & Xia, H. (2021). Incremental vs. breakthrough innovation: The role of technology spillovers. *Management Science, 67*(3), 1779–1802. https://doi.org/10.1287/mnsc.2019.3507

Chan, K. J. D., Papyshev, G., & Yarime, M. (2024). Balancing the tradeoff between regulation and innovation for artificial intelligence: An analysis of top-down command and control and bottom-up self-regulatory approaches. *Technology in Society, 79*, Article 102747. https://doi.org/10.1016/j.techsoc.2024.102747

Chen, L., Chen, Z., Zhang, Y., Liu, Y., Osman, A. I., Farghali, M., Hua, J., Al-Fatesh, A., Ihara, I., Rooney, D. W., & Yap, P.-S. (2023). Artificial intelligence-based solutions for climate change: A review. *Environmental Chemistry Letters, 21*(5), 2525–2557. https://doi.org/10.1007/s10311-023-01617-y

Choi, J., & Yoon, J. (2022). Measuring knowledge exploration distance at the patent level: Application of network embedding and citation analysis. *Journal of Informetrics, 16*(2), Article 101286. https://doi.org/10.1016/j.joi.2022.101286

Chotia, V., Cheng, Y., Agarwal, R., & Vishnoi, S. K. (2024). AI-enabled green business strategy: Path to carbon neutrality via environmental performance and green process innovation. *Technological Forecasting and Social Change, 202*, Article 123315. https://doi.org/10.1016/j.techfore.2024.123315

Cicerone, G., Faggian, A., Montresor, S., & Rentocchini, F. (2023). Regional artificial intelligence and the geography of environmental technologies: Does local AI knowledge help regional green-tech specialization? *Regional Studies, 57*(2), 330–343. https://doi.org/10.1080/00343404.2022.2092610

Cockburn, I. M., Henderson, R., & Stern, S. (2019). 4. The impact of artificial intelligence on innovation: An exploratory analysis. In *The economics of artificial intelligence* (pp. 115–148). University of Chicago Press. https://www.degruyterbrill.com/document/doi/10.7208/9780226613475-006/pdf?licenseType=restricted.

Coeckelbergh, M., & Sætra, H. S. (2023). Climate change and the political pathways of AI: The technocracy-democracy dilemma in light of artificial intelligence and human agency. *Technology in Society, 75*, Article 102406. https://doi.org/10.1016/j.techsoc.2023.102406

Cohen, L., Gurun, U. G., & Nguyen, Q. H. (2020). *The ESG-Innovation disconnect: Evidence from green patenting (Working paper no. 27990)*. National Bureau of Economic Research. https://doi.org/10.3386/w27990

Crafts, N. (2021). Artificial intelligence as a general-purpose technology: An historical perspective. https://doi.org/10.1093/oxrep/grab012'%255D.

Creutzig, F., Acemoglu, D., Bai, X., Edwards, P. N., Hintz, M. J., Kaack, L. H., Kilkis, S., Kunkel, S., Luers, A., Milojevic-Dupont, N., Rejeski, D., Renn, J., Rolnick, D., Rosol, C., Russ, D., Turnbull, T., Verdolini, E., Wagner, F., Wilson, C., … Zumwald, M. (2022). Digitalization and the anthropocene. *Annual Review of Environment and Resources, 47*(47), 479–509. https://doi.org/10.1146/annurev-environ-120920-100056, 2022.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers) (pp. 4171-4186).

Deloitte Global. (2024). *Powering AI*. Deloitte Global. https://www.deloitte.com/global/en/issues/climate/powering-ai.html.

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research, 121*, 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019

Diodato, D., Huergo, E., Moncada-Paternò-Castello, P., Rentocchini, F., & Timmermans, B. (2023). Introduction to the special issue on "the twin (digital and green) transition: Handling the economic and social challenges.". *Industry & Innovation, 30*(7), 755–765. https://doi.org/10.1080/13662716.2023.2254272

Edwards, D., Cooper, Z. G. T., & Hogan, M. (2024). The making of critical data center studies. *Convergence: The International Journal of Research Into New Media Technologies, 31*(2), Article 13548565231224157. https://doi.org/10.1177/13548565231224157

European Commission. (2022). 2022 strategic foresight report—european commission. https://commission.europa.eu/strategy-and-policy/strategic-foresight/2022-strategic-foresight-report_en.

Faggian, A., Marzucchi, A., & Montresor, S. (2025). Regions facing the 'twin transition': Combining regional green and digital innovations. *Regional Studies, 59*(1), Article 2398555. https://doi.org/10.1080/00343404.2024.2398555

Feng, S. (2020). The proximity of ideas: An analysis of patent text using machine learning. *PLoS One, 15*(7), Article e0234880. https://doi.org/10.1371/journal.pone.0234880

Fleiß, E., Hatzl, S., & Rauscher, J. (2024). Smart energy technology: A survey of adoption by individuals and the enabling potential of the technologies. *Technology in Society, 76*, Article 102409. https://doi.org/10.1016/j.techsoc.2023.102409

Fouquet, R., & Hippe, R. (2022). Twin transitions of decarbonisation and digitalisation: A historical perspective on energy and information in European economies. *Energy Research & Social Science, 91*, Article 102736. https://doi.org/10.1016/j.erss.2022.102736

Fredström, A., Wincent, J., Sjödin, D., Oghazi, P., & Parida, V. (2021). Tracking innovation diffusion: AI analysis of large-scale patent data towards an agenda for further research. *Technological Forecasting and Social Change, 165*, Article 120524. https://doi.org/10.1016/j.techfore.2020.120524

Freunek, M., & Niggli, M. (2023). Introducing DynaPTI–constructing a dynamic patent technology indicator using text mining and machine learning. *Frontiers in Artificial Intelligence, 6*. https://doi.org/10.3389/frai.2023.1136846

Fusillo, F. (2023). Green technologies and diversity in the knowledge search and output phases: Evidence from european patents. *Research Policy, 52*(4), Article 104727. https://doi.org/10.1016/j.respol.2023.104727

Fusillo, F., Quatraro, F., & Usai, S. (2022). Going green: The dynamics of green technological alliances. *Economics of Innovation and New Technology, 31*(5), 362–386. https://doi.org/10.1080/10438599.2020.1799143

Garrido-Merchán, E. C., González-Barthe, C., & Vaca, M. C. (2023). *Fine-tuning ClimateBert transformer with ClimaText for the disclosure analysis of climate-related financial risks* (No. arXiv:2303.13373). *arXiv*. https://doi.org/10.48550/arXiv.2303.13373

Ge, V. (2022). GE using AI/ML to reduce wind turbine logistics and installation costs | GE vernova news. https://www.gevernova.com/news/press-releases/ge-using-aiml-to-reduce-wind-turbine-logistics-and-installation-costs.

Gibney. (2022). How to shrink AI's ballooning carbon footprint. https://www.nature.com/articles/d41586-022-01983-7.

Giczy, A. V., Pairolero, N. A., & Toole, A. A. (2022). Identifying artificial intelligence (AI) invention: A novel AI patent dataset. *The Journal of Technology Transfer, 47*(2), 476–505. https://doi.org/10.1007/s10961-021-09900-2

Golombek, R., Lind, A., Ringkjøb, H.-K., & Seljom, P. (2022). The role of transmission and energy storage in European decarbonization towards 2050. *Energy, 239*, Article 122159. https://doi.org/10.1016/j.energy.2021.122159

Habibollahi Najaf Abadi, H., & Pecht, M. (2020). Artificial intelligence trends based on the patents granted by the United States patent and trademark office. *IEEE Access, 8*, 81633–81643. https://doi.org/10.1109/ACCESS.2020.2988815

Haghighian Roudsari, A., Afshar, J., Lee, W., & Lee, S. (2022). PatentNet: Multi-label classification of patent documents using deep learning based language understanding. *Scientometrics, 127*(1), 207–231. https://doi.org/10.1007/s11192-021-04179-4

Hall, B. H., & Helmers, C. (2019). The impact of international patent systems: Evidence from accession to the European patent convention. *Research Policy, 48*(9), Article 103810. https://doi.org/10.1016/j.respol.2019.103810

Hasan, M. K., Mahmud, M., Ahasan Habib, A. K. M., Motakabber, S. M. A., & Islam, S. (2021). Review of electric vehicle energy storage and management system: Standards, issues, and challenges. *Journal of Energy Storage, 41*, Article 102940. https://doi.org/10.1016/j.est.2021.102940

Herman, K. S. (2022). Beyond the UNFCCC North-South divide: How newly industrializing countries collaborate to innovate in climate technologies. *Journal of Environmental Management, 309*, Article 114425. https://doi.org/10.1016/j.jenvman.2021.114425

Herman, K. S., Chen, C.-F., & Sovacool, B. K. (2024). Framing industrial decarbonization technologies in the public sphere: Narratives from the digital 'town square' in the United Kingdom. *Environmental Research Communications, 6*(12), Article 125006. https://doi.org/10.1088/2515-7620/ad9891

Herman, K. S., Hall, J. K., Sovacool, B. K., & Iskandarova, M. (2025). The industrial decarbonization paradigm: Carbon lock-in or path renewal in the United Kingdom? *Ecological Economics, 235*, Article 108628. https://doi.org/10.1016/j.ecolecon.2025.108628

Herman, K. S., Sovacool, B. K., Geels, F. W., & Iskandarova, M. (2025). Navigating reconfiguration and systems disruption: Decarbonization pathways for UK industrial clusters. *Energy, 328*, Article 136464. https://doi.org/10.1016/j.energy.2025.136464

Herman, K. S., & Xiang, J. (2019). Induced innovation in clean energy technologies from foreign environmental policy stringency? *Technological Forecasting and Social Change, 147*, 198–207. https://doi.org/10.1016/j.techfore.2019.07.006

Herman, K. S., & Xiang, J. (2020). Environmental regulatory spillovers, institutions, and clean technology innovation: A panel of 32 countries over 16 years. *Energy Research & Social Science, 62*, Article 101363. https://doi.org/10.1016/j.erss.2019.101363

Herman, K. S., & Xiang, J. (2022a). Channeled through trade: How foreign environmental regulations induce domestic renewable energy innovation. *Energy Research & Social Science, 89*, Article 102629. https://doi.org/10.1016/j.erss.2022.102629

Herman, K. S., & Xiang, J. (2022b). How collaboration with G7 countries drives environmental technology innovation in ten newly industrializing countries. *Energy for Sustainable Development, 71*, 176–185. https://doi.org/10.1016/j.esd.2022.09.011

Higham, K., de Rassenfosse, G., & Jaffe, A. B. (2021). Patent quality: Towards a systematic framework for analysis and measurement. *Research Policy, 50*(4), Article 104215. https://doi.org/10.1016/j.respol.2021.104215

Hoefler, T., Hendel, A., & Roweth, D. (2022). The convergence of hyperscale data center and high-performance computing networks. *Computer, 55*(7), 29–37. https://doi.org/10.1109/MC.2022.3158437

Hopp, J. Z. (2025). Contrasting directionalities in responsible innovation, lessons from the salmon farming industry in Chile and Norway. *Technology in Society, 82*, Article 102946. https://doi.org/10.1016/j.techsoc.2025.102946

Hötte, K., & Jee, S. J. (2022). Knowledge for a warmer world: A patent analysis of climate change adaptation technologies. *Technological Forecasting and Social Change, 183*, Article 121879. https://doi.org/10.1016/j.techfore.2022.121879

Hussain, M., Alamri, A., Zhang, T., & Jamil, I. (2024). Application of artificial intelligence in the oil and gas industry. In A. Chakir, J. F. Andry, A. Ullah, R. Bansal, & M. Ghazouani (Eds.), *Engineering applications of artificial intelligence* (pp. 341–373). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-50300-9_19

IEA. (2025a). Energy and AI – Analysis. https://www.iea.org/reports/energy-and-ai.

IEA. (2025b). *The state of energy innovation*. IEA. https://www.iea.org/reports/the-state-of-energy-innovation.

Igna, I., & Venturini, F. (2023). The determinants of AI innovation across European firms. *Research Policy, 52*(2), Article 104661. https://doi.org/10.1016/j.respol.2022.104661

Jaffe, A. B., Newell, R. G., & Stavins, R. N. (2005). A tale of two market failures: Technology and environmental policy. *Ecological Economics, 54*(2–3), 164–174. https://doi.org/10.1016/j.ecolecon.2004.12.027

Jiang, L., Zhang, C., Scherz, P. A., & Goetz, S. (2024). *Can large language models generate high-quality patent claims?* (No. arXiv:2406.19465). *arXiv*. https://doi.org/10.48550/arXiv.2406.19465

Johnstone, N., Haščič, I., & Popp, D. (2010). Renewable energy policies and technological innovation: Evidence based on patent counts. *Environmental and Resource Economics, 45*(1), 133–155. https://doi.org/10.1007/s10640-009-9309-1

Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change, 12*(6), 518–527. https://doi.org/10.1038/s41558-022-01377-7

Kopka, A., & Grashof, N. (2022). Artificial intelligence: Catalyst or barrier on the path to sustainability? *Technological Forecasting and Social Change, 175*, Article 121318. https://doi.org/10.1016/j.techfore.2021.121318

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems, 25*. https://proceedings.neurips.cc/paper/2012/hash/c399862d3b9d6b76c8436e924a68c45b-Abstract.html.

Kus, B., & Jackson, G. (2025). Green transitions: Rethinking political economy in the context of climate change. *Regulation & Governance, 19*(2), 287–302. https://doi.org/10.1111/rego.70013

Lannelongue, L., Grealey, J., & Inouye, M. (2021). Green algorithms: Quantifying the carbon footprint of computation. *Advanced Science, 8*(12), Article 2100707. https://doi.org/10.1002/advs.202100707

Laplume, A. O., Pathak, S., & Xavier-Oliveira, E. (2014). The politics of intellectual property rights regimes: An empirical study of new technology use in entrepreneurship. *Technovation, 34*(12), 807–816. https://doi.org/10.1016/j.technovation.2014.07.006

Lee, J.-S., & Hsiang, J. (2020). Patent classification by fine-tuning BERT language model. *World Patent Information, 61*, Article 101965. https://doi.org/10.1016/j.wpi.2020.101965

Lee, J.-H., & Woo, J. (2020). Green new deal policy of South Korea: Policy innovation for a sustainability transition. *Sustainability, 12*(23). https://doi.org/10.3390/su122310191. Article 23.

Levine, D. S., & Sichelman, T. (2018). Why do startups use trade secrets. *The Notre Dame Law Review, 94*, 751.

Li, J., Hania, A., Yahya, F., Hussain, M., & Waqas, M. (2025). Fostering sustainable futures through global peace and eco-innovation: A cross-country evidence. *Technology in Society, 83*, Article 103008. https://doi.org/10.1016/j.techsoc.2025.103008

Lin, X., & Sovacool, B. K. (2020). Inter-niche competition on ice? Socio-technical drivers, benefits and barriers of the electric vehicle transition in Iceland. *Environmental Innovation and Societal Transitions, 35*, 1–20. https://doi.org/10.1016/j.eist.2020.01.013

Liu, K., Wei, Z., Zhang, C., Shang, Y., Teodorescu, R., & Han, Q.-L. (2022). Towards long lifetime battery: AI-based manufacturing and management. *IEEE/CAA Journal of Automatica Sinica, 9*(7), 1139–1165. https://doi.org/10.1109/JAS.2022.105599

Lopolito, A., Falcone, P. M., & Sica, E. (2022). The role of proximity in sustainability transitions: A technological niche evolution analysis. *Research Policy, 51*(3), Article 104464. https://doi.org/10.1016/j.respol.2021.104464

Luers, A., Koomey, J., Masanet, E., Gaffney, O., Creutzig, F., Lavista Ferres, J., & Horvitz, E. (2024). Will AI accelerate or delay the race to net-zero emissions? *Nature, 628*(8009), 718–720. https://doi.org/10.1038/d41586-024-01137-x

Luitse, D., & Denkena, W. (2021). The great transformer: Examining the role of large language models in the political economy of AI. *Big Data & Society, 8*(2), Article 20539517211047734. https://doi.org/10.1177/20539517211047734

Manmatharasan, P., Bitsuamlak, G., & Grolinger, K. (2025). AI-driven design optimization for sustainable buildings: A systematic review. *Energy and Buildings, 332*, Article 115440. https://doi.org/10.1016/j.enbuild.2025.115440

Mao, S., Wang, B., Tang, Y., & Qian, F. (2019). Opportunities and challenges of artificial intelligence for green manufacturing in the process industry. *Engineering, 5*(6), 995–1002. https://doi.org/10.1016/j.eng.2019.08.013

Marín-Vinuesa, L. M., Scarpellini, S., Portillo-Tarragona, P., & Moneva, J. M. (2020). The impact of eco-innovation on performance through the measurement of financial resources and green patents. *Organization & Environment, 33*(2), 285–310. https://doi.org/10.1177/1086026618819103

Marx, M., & Fuegi, A. (2020). Reliance on science: Worldwide front-page patent citations to scientific articles. *Strategic Management Journal, 41*(9), 1572–1594. https://doi.org/10.1002/smj.3145

Maslej, N., Fattorini, L., Perrault, R., et al. (2025). *The AI Index 2025 Annual Report*. Stanford, CA: Stanford Institute for Human-Centered Artificial Intelligence. https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf.

Memari, M., Shakya, P., Shekaramiz, M., Seibi, A. C., & Masoum, M. A. S. (2024). Review on the advancements in wind turbine blade inspection: Integrating drone and deep learning technologies for enhanced defect detection. *IEEE Access, 12*, 33236–33282. https://doi.org/10.1109/ACCESS.2024.3371493

METI. (2022). Climate change/METI ministry of economy, trade and industry. https://www.meti.go.jp/english/policy/energy_environment/global_warming/index.html.

Montresor, S., & Vezzani, A. (2023). Digital technologies and eco-innovation. Evidence of the twin transition from Italian firms. *Industry & Innovation, 30*(7), 766–800. https://doi.org/10.1080/13662716.2023.2213179

Movsessian, A., García Cava, D., & Tcherniak, D. (2021). An artificial neural network methodology for damage detection: Demonstration on an operating wind turbine blade. *Mechanical Systems and Signal Processing, 159*, Article 107766. https://doi.org/10.1016/j.ymssp.2021.107766

Nadim, K., Ouali, M.-S., Ghezzaz, H., & Ragab, A. (2023). Learn-to-supervise: Causal reinforcement learning for high-level control in industrial processes. *Engineering Applications of Artificial Intelligence, 126*, Article 106853. https://doi.org/10.1016/j.engappai.2023.106853

Nair, P., Vakharia, V., Shah, M., Kumar, Y., Woźniak, M., Shafi, J., & Fazal Ijaz, M. (2024). AI-Driven digital twin model for reliable lithium-ion battery discharge capacity predictions. *International Journal of Intelligent Systems, 2024*(1), Article 8185044. https://doi.org/10.1155/2024/8185044

Nasir, O., Javed, R. T., Gupta, S., Vinuesa, R., & Qadir, J. (2023). Artificial intelligence and sustainable development goals nexus via four vantage points. *Technology in Society, 72*, Article 102171. https://doi.org/10.1016/j.techsoc.2022.102171

Nesta, asf_core_data (Python package), Nesta, 2024. Available at: https://github.com/nestauk/asf_core_data.

Ochieng, E. G., Ominde, D., & Zuofa, T. (2024). Potential application of generative artificial intelligence and machine learning algorithm in oil and gas sector: Benefits and future prospects. *Technology in Society, 79*, Article 102710. https://doi.org/10.1016/j.techsoc.2024.102710

OECD. (2015). *Measuring environmental innovation using patent data (OECD environment working papers No. 89; OECD environment working papers* (Vol. 89). https://doi.org/10.1787/5js009kf48xw-en

Ooms, W., & Piepenbrink, R. (2021). Open innovation for wicked problems: Using proximity to overcome barriers. *California Management Review, 63*(2), 62–100. https://doi.org/10.1177/0008125620968636

Orsatti, G., Quatraro, F., & Pezzoni, M. (2020). The antecedents of green technologies: The role of team-level recombinant capabilities. *Research Policy, 49*(3), Article 103919. https://doi.org/10.1016/j.respol.2019.103919

Pairolero, N. A., Giczy, A. V., Torres, G., Erana, T. I., Finlayson, M. A., & Toole, A. A. (2025). The artificial intelligence patent dataset (AIPD) 2023 update. *Technology in Society, 50*, 2587–2610.

Patterson, S., & Teh, Y. W. (2013). Stochastic gradient riemannian langevin dynamics on the probability simplex. *Advances in Neural Information Processing Systems, 26*. https://proceedings.neurips.cc/paper_files/paper/2013/hash/309928d4b100a5d75adff48a9bfc1ddb-Abstract.html.

Pavitt, K. (2002). Innovating routines in the business firm: What corporate tasks should they be accomplishing? *Industrial and Corporate Change, 11*(1), 117–133. https://doi.org/10.1093/icc/11.1.117

Pelaez, S., Verma, G., Ribeiro, B., & Shapira, P. (2024). Large-scale text analysis using generative language models: A case study in discovering public value expressions in AI patents. *Quantitative Science Studies, 5*(1), 153–169. https://doi.org/10.1162/qss_a_00285

Petrakis, K. (2023). *Patent Inspector* [Python]. https://github.com/KonstantinosPetrakis/PatentInspector (Original work published 2022).

Qi, J., Lei, L., Zheng, K., & Wang, X. (2020). Patent analytic citation-based VSM: Challenges and applications. *IEEE Access, 8*, 17464–17476. https://doi.org/10.1109/ACCESS.2020.2967817

Rehman, S. U., Giordino, D., Zhang, Q., & Alam, G. M. (2023). Twin transitions & industry 4.0: Unpacking the relationship between digital and green factors to determine green competitive advantage. *Technology in Society, 73*, Article 102227. https://doi.org/10.1016/j.techsoc.2023.102227

Rezazadegan, R., Sharifzadeh, M., & Magee, C. L. (2024). Quantifying the progress of artificial intelligence subdomains using the patent citation network. *Scientometrics, 129*(5), 2559–2581. https://doi.org/10.1007/s11192-024-04996-3

Rodriguez-Sanchez, C., Sancho-Esper, F. M., Casaló, L. V., & López, M. (2025). Generative AI as a source of information on environmental problems: Understanding its influence on generation Z. *Technology in Society, 83*, Article 103036. https://doi.org/10.1016/j.techsoc.2025.103036

Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A. S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A. S., Maharaj, T., Sherwin, E. D., Mukkavilli, S. K., Kording, K. P., Gomes, C. P., Ng, A. Y., Hassabis, D., Platt, J. C., … Bengio, Y. (2022). Tackling climate change with machine learning. *ACM Computing Surveys, 55*(2). https://doi.org/10.1145/3485128, 42:1-42:96.

Sareen, S., & Haarstad, H. (2021). Digitalization as a driver of transformative environmental innovation. *Environmental Innovation and Societal Transitions, 41*, 93–95. https://doi.org/10.1016/j.eist.2021.09.016

Schneider Electric. (2024). AI-powered HVAC in educational buildings: A net digital impact use case. *Schneider electric*. https://www.se.com/ww/en/insights/sustainability/sustainability-research-institute/ai-powered-hvac-in-educational-buildings/.

Solarin, S. A., Kazak, H., Shahbaz, M., Akcan, A. T., & Selcuk, H. (2025). Convergence of environmental innovation in Europe with or without United Kingdom: Technological implications for the environment. *Technology in Society, 83*, Article 103047. https://doi.org/10.1016/j.techsoc.2025.103047

Sovacool, B. K., Del Rio, D. F., Herman, K., Iskandarova, M., Uratani, J. M., & Griffiths, S. (2024). Reconfiguring European industry for net-zero: A qualitative review of hydrogen and carbon capture utilization and storage benefits and implementation challenges. *Energy & Environmental Science, 17*(10), 3523–3569. https://doi.org/10.1039/D3EE03270A

Squicciarini, et al. (2013). *Measuring patent quality*. OECD https://www.oecd.org/en/publications/measuring-patent-quality_5k4522wkw1r8-en.html.

Stanford University. (2023). The 2023 AI index report | stanford HAI. https://hai.stanford.edu/ai-index/2023-ai-index-report.

Tan, B., & Chen, Y. (2025). Decarbonization pressure and business performance under the background of carbon neutrality – Evidence from industrial carbon lock-in. *Energy Reports, 13*, 5151–5159. https://doi.org/10.1016/j.egyr.2025.04.057

Toole, A. A., Pairolero, N., Forman, J., & Giczy, A. (2020). The promise of machine learning for patent landscaping. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3555834

Trappey, A. J. C., Trappey, C. V., Wu, J.-L., & Wang, J. W. C. (2020). Intelligent compilation of patent summaries using machine learning and natural language processing techniques. *Advanced Engineering Informatics, 43*, Article 101027. https://doi.org/10.1016/j.aei.2019.101027

UK CCC. (2024). Progress in reducing emissions 2024 report to parliament. *Climate change committee*. https://www.theccc.org.uk/publication/progress-in-reducing-emissions-2024-report-to-parliament/.

U.S. Department of Energy, Artificial intelligence for energy, Energy.gov, 2024. Available at: https://www.energy.gov/topics/artificial-intelligence-energy.

USPTO. (2025). API purpose | PatentsView. https://patentsview.org/apis/purpose.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., … Polosukhin, I. (2017). *Attention is all you need. Advances in neural information processing systems, 30*.

Verendel, V. (2021). Tracking AI in climate innovation. https://doi.org/10.21203/rs.3.rs-1152592/v1.

Vergou, E., Pagouni, I., Nanos, M., & Kermanidis, K. L. (2023). Readability classification with wikipedia data and All-MiniLM embeddings. In I. Maglogiannis, L. Iliadis, A. Papaleonidas, & I. Chochliouros (Eds.), *Artificial intelligence applications and innovations. AIAI 2023 IFIP WG 12.5 international workshops* (pp. 369–380). Nature Switzerland: Springer. https://doi.org/10.1007/978-3-031-34171-7_30.

Verrier, B., & Strachan, N. (2024). Sunset and sunrise business strategies shaping national energy transitions. *Renewable and Sustainable Energy Reviews, 195*, Article 114330. https://doi.org/10.1016/j.rser.2024.114330

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the sustainable development goals. *Nature Communications, 11*(1), 233. https://doi.org/10.1038/s41467-019-14108-y

Wang, J., Liu, Y., Wang, W., & Wu, H. (2024). Does artificial intelligence improve enterprise carbon emission performance? Evidence from an intelligent transformation policy in China. *Technology in Society, 79*, Article 102751. https://doi.org/10.1016/j.techsoc.2024.102751

Wang, H., Liu, Y., Zhou, B., Li, C., Cao, G., Voropai, N., & Barakhtenko, E. (2020). Taxonomy research of artificial intelligence for deterministic solar power forecasting. *Energy Conversion and Management, 214*, Article 112909. https://doi.org/10.1016/j.enconman.2020.112909

Wang, Q., Sun, T., & Li, R. (2023). Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects. *Energy & Environment, 36*(2), Article 0958305X231220520. https://doi.org/10.1177/0958305X231220520

Wang, S., & Zhang, H. (2025). Generative artificial intelligence and internationalization green innovation: Roles of supply chain innovations and AI regulation for SMEs. *Technology in Society, 82*, Article 102898. https://doi.org/10.1016/j.techsoc.2025.102898

Webersinke, N., Kraus, M., Bingler, J. A., & Leippold, M. (2022). *ClimateBert: A pretrained language model for climate-related text* (No. arXiv:2110.12010). *arXiv*. https://doi.org/10.48550/arXiv.2110.12010

Whalen, R., Lungeanu, A., DeChurch, L., & Contractor, N. (2020). Patent similarity data and innovation metrics. *Journal of Empirical Legal Studies, 17*(3), 615–639. https://doi.org/10.1111/jels.12261

WIPO. (2024). WIPO green – The marketplace for sustainable technology. https://www3.wipo.int/wipogreen/en/.

WIPO Green. (2024). Wipogreen database. https://wipogreen.wipo.int/wipogreen-database/database.

Xiang, W., Tran, H.-D., & Johnson, T. T. (2017). Reachable set computation and safety verification for neural networks with ReLU activations. No. arXiv:1712.08163). arXiv https://doi.org/10.48550/arXiv.1712.08163.

Xin, L., Ahmad, M., & Khattak, S. I. (2023). Impact of innovation in hybrid electric vehicles-related technologies on carbon dioxide emissions in the 15 most innovative countries. *Technological Forecasting and Social Change, 196*, Article 122859. https://doi.org/10.1016/j.techfore.2023.122859

Yin, K., Cai, F., & Huang, C. (2022). How does artificial intelligence development affect green technology innovation in China? Evidence from dynamic panel data analysis. *Environmental Science and Pollution Research, 30*(10), 28066–28090. https://doi.org/10.1007/s11356-022-24088-0

Yu, L., Liu, B., Lin, Q., Zhao, X., & Che, C. (2024a). Semantic similarity matching for patent documents using ensemble BERT-related model and novel text processing method (No. arXiv:2401.06782). arXiv https://doi.org/10.48550/arXiv.2401.06782.

Yu, L., Liu, B., Lin, Q., Zhao, X., & Che, C. (2024b). Similarity matching for patent documents using ensemble BERT-related model and novel text processing method. *Journal of Advances in Information Technology, 15*(3), 446–450. https://doi.org/10.12720/jait.15.3.446-450

Zu, X., Ni, G., & Hu, R. (2025). AI technology innovation, knowledge management and corporate environmental sustainability: Evidence from Chinese patent data. *Technology in Society, 83*, Article 102984. https://doi.org/10.1016/j.techsoc.2025.102984

Zumofen, G. (2025). Combining a conjoint experiment and machine learning model to include end-users in a constructive technology assessment: The case of seasonal thermal energy storage. *Technology in Society, 81*, Article 102833. https://doi.org/10.1016/j.techsoc.2025.102833