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Artificial intelligence for climate change: a patent analysis in the manufacturing sector

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ABSTRACT

This study analyzes the current state of artificial intelligence (AI) technologies for addressing and mitigating climate change in the manufacturing sector and provides an outlook on future developments. The research is grounded in the concept of general-purpose technologies (GPTs), motivated by a still limited understanding of innovation patterns for this application context. To this end, we focus on global patenting activity between 2011 and 2023 (5,919 granted patents classified for "mitigation or adaptation against climate change" in the "production or processing of goods"). We examined time trends, applicant characteristics, and underlying technologies. A topic modeling analysis was performed to identify emerging themes from the unstructured textual data of the patent abstracts. This allowed the identification of six AI application domains. For each of them, we built a network analysis and ran growth trend and forecasting models. Our results show that patenting activities are mostly oriented toward improving the efficiency and reliability of manufacturing processes in five out of six identified domains ("predictive analytics", "material sorting", "defect detection", "advanced robotics", and "scheduling"). Instead, AI within the "resource optimization" domain relates to energy management, showing an interplay with other climate-related technologies. Our results also highlight interdependent innovations peculiar to each domain around core AI technologies. Forecasts show that the more specific technologies are within domains, the longer it will take for them to mature. From a practical standpoint, the study sheds light on the role of AI within the broader cleantech innovation landscape and urges policymakers to consider synergies. Managers can find information to define technology portfolios and alliances considering technological co-evolution.

Index Terms — artificial intelligence, AI, climate change, sustainability, patent analysis, technology foresight

JEL Codes — O14, O31, O32, O33, O34

1. Introduction

Addressing climate change is at the top of policymakers' agendas worldwide, and there are growing expectations of effective action [1]. The ever-increasing number of extreme weather events and the severe consequences of long-term alterations to weather patterns come with a spectrum of social challenges, economic instability, and adverse effects on food production and safety [2], [3], [4]. Together with more sustainable consumption patterns, an important factor to minimize–and potentially offset–the environmental impact of anthropic activities is technology [5], [6]. Alongside new process technologies, materials, and solutions for carbon capture and storage, AI is being hailed for its transformative potential across different sectors [7].

Unlike other innovations with specific areas of application, AI is considered a general purpose technology because it exhibits characteristics that allow it to fundamentally transform various aspects of the economy and society [8], [9], [10]. Its ubiquity across sectors, fast-paced growth rate, and spill-over effects have fueled significant expectations also concerning climate change [7], [11], [12]. However, despite the positive outlook, the actual development of AI solutions to address climate change remains an element of academic and industrial conjecture [13]. This uncertainty leads to three main issues. First, when considering the investments needed to develop AI, organizations struggle to determine where to direct their efforts due to a limited understanding of the current progress and innovation dynamics [14], [15]. Second, on the adoption side, firms are faced with a limited awareness of emerging technological trajectories, which makes it challenging for them to explore and experiment with AI [16]. Third, policymakers lack a comprehensive dashboard to inform their actions, such as allocating budgets and providing financial incentives for firms [17]. This shortfall extends to their ability to verify the effectiveness of initiatives aimed at sustaining a green and digital transition [18], [19].

When analyzing the technological landscape of a GPT, it is important to focus on the interplay between a core technology stack and the innovations being developed within application sectors, which are often remote and difficult to coordinate [20]. With respect to AI, the picture is rather clear in the consumer sector [21], [10], whereas others have received comparatively less attention. This is problematic because there might be sector-specific trajectories, as technology development is normally dispersed throughout the economy, requiring tailoring of innovation programs and incentives [20]. Further specificities might emerge in technology developed for addressing or mitigating climate change due to complexities and interdependencies [22]. Research on the actual innovation landscape in this respect is needed to balance the risk of unjustified techno-optimism with actual evidence, thus providing substantiated input to climate policy.

The aim of this study is to answer the following research questions (RQs):

RQ1. What are the characteristics of the innovation landscape with respect to AI applications for climate change mitigation and adaptation in manufacturing?

RQ2. What is the evolution over time of such applications?

We place manufacturing at the center of our inquiry for two reasons. First, according to recent data provided by the World Economic Forum (WEF) [23] and the United Nations (UN) [24], manufacturing activities represent a major cause of climate change. Beyond the significant emissions of greenhouse gases (23% of the total – [23]), industries involved in goods production contribute to the unsustainable consumption of natural resources: their extensive use of water, raw materials, and energy depletes the Earth's natural reserves and leads to ecological imbalances [25]. The burden is compounded by the waste generated by these activities [26]. Second, environmental sustainability in manufacturing is increasingly at the forefront of global discourse, largely driven by pressing consumer and stakeholder demands [27], [28]. Despite mounting expectations, however, the development of AI solutions to address climate change in manufacturing is still an unexplored area in the literature [11]. Moreover, available and upcoming AI applications for manufacturing might not match current expectations, an aspect echoed by Nishant et al. [29], who observed that the ambitious promises of cutting-edge technologies often fail to fully materialize in tangible applications.

Through an in-depth patent analysis of AI solutions to address climate change in manufacturing (a population of 5,919 patents granted worldwide between 2011 and 2023), we were able to provide an evidence-based understanding of the state-of-the-art, past evolution, and future trends of AI in this context. A patent analysis goes indeed a step further than academic reviews: it provides a systematic overview of real-world trends, including technological interdependencies, main players, and evolution [17], [30]. As a result, patent analysis enables a more precise portrait of how technology is being practically developed [31], [32]. The analysis was built using several techniques including descriptive statistics, topic modeling, network analysis, and growth trend and forecasting models. The results highlight a significant growth in the number of patents and different innovator profiles in terms of country (e.g., China stands out as the leading country in terms of patenting activity) as well as of individual organizations (e.g., specialized vs. broad portfolio players). Six main application domains emerge from the data: predictive analytics, material sorting, defect detection, advanced robotics, scheduling, and resource optimization. As can be expected for a GPT [33], [34], these domains build on the combination of a set of core International Patent Classification (IPC) codes together with specialized technologies and are characterized by a diverse and staggered progression toward maturity.

By moving beyond speculation, the study helps to illuminate the actual domains of AI development. Our main contribution is to temper the hype around AI with an evidence-based assessment [35], [36]. This is crucial for effectively bridging the gap between expectations and actual advancements, gaining valuable insights about "*the real meaning and functionality*" of AI [37]. A clear understanding of the research and development (R&D) arena can also help to assess the influence of specific knowledge interactions, providing a foundation for identifying how collaborative efforts between academia, industry, and policymakers can accelerate the integration of AI in manufacturing for sustainability [38], [39]. The findings contribute to the academic discourse on AI as a GPT and hold practical implications for industry stakeholders, offering a nuanced understanding of technological trends crucial for addressing climate change challenges. This could help both researchers and managers in directing further investigations and R&D activities at the crossroads between AI and sustainability.

The rest of this article is organized as follows. The next section presents AI and its implications for climate change. Section 3 illustrates the methodology. Section 4 and Section 5 present and discuss the findings. To conclude, Section 6 outlines the contributions and limitations of the study.

2. Background

2.1. AI as a GPT

Defined as *"[...] mechanisms underlying thought and intelligent behavior and their embodiment in machines"* [40], AI represents the pinnacle of computational technology's quest to mimic and potentially surpass human intelligence. It encompasses a wide range of capabilities, from learning and reasoning to problem-solving and language comprehension [41]. Since the concept of AI was first introduced to the public in the 1950s, its history has been characterized by waves of excitement and periods of disillusionment [42]. Recently, the interest in AI has increased, driven by the release of generative tools for non-technical users (e.g., ChatGPT – [43], [44]). AI can efficiently and effectively process large data sets and make sense of unstructured data, also working in real-time

[45], [46]. This results in data-driven insights in support of managerial decision-making as well as in the automation of several tasks [47]. The ability to process and analyze information at such a scale enables AI to unravel complex patterns and promises to revolutionize fields such as medicine, financial services, urban planning, agriculture, education, energy, and manufacturing [11], [48], [49]. Forecasts show an ever-increasing penetration of AI across these domains. For example, the global adoption of AI by organizations is expected to grow by 40% between 2023 and 2030 [50], with four out of five companies considering it a top priority in their business strategy [51].

AI is increasingly recognized as a GPT [21], [10], [52]. Prior examples of GPTs include the steam engine, electricity, and computing technologies, which are well-established examples of technologies with a radical impact on human history [20]. According to Jovanovic and Rousseau [53], GPTs have three main characteristics: pervasiveness across industrial sectors and in society, technological dynamism leading to steady performance improvement, and innovation spawning new products and processes. When considering AI, current research recognizes its wide range of applications in relation to data processing for predictive purposes, the augmentation of human tasks, and the automation of activities [54]. Moreover, as seen for digital transformation with respect to prior-generation computing and information systems, AI's general applicability is enhanced by its non-rival nature against existing technologies, which supports a comparatively faster growth in the number of new users than is observed for physical GPTs [55].

In general, the literature has shown the presence of a "productivity paradox" in relation to GPTs [8], [9], [34]. On the one hand, these technologies come with the promise of substantial improvements in products and processes alike, fueling expectations about positive impacts on economic growth. On the other hand, aggregated statistics hardly show any productivity improvement in the short term, as GPTs often enter established socio-technical systems characterized by complementary technologies, infrastructures, and (inter)organizational practices and routines. These aspects have only partially been considered insofar as, by and large, AI has entered into already digitalized domains, with the most innovative applications being developed in the consumer sector [21]. Under these circumstances, the need for organizational adjustments and visibility into system-level implications was lower, as AI development was driven by technology giants in the Internet space [10].

However, as AI spreads across application sectors, it is increasingly important to investigate technological and non-technological interdependencies. Indeed, recent surveys [56], [57], [58] report that the transition to AI in manufacturing is fraught with several critical concerns. First, some drawbacks stem from the need to integrate a wide range of protocols: achieving a seamless and efficient fusion of these disparate systems that are often crafted independently necessitates relevant standardization and synchronization efforts [59], [60]. Second, AI tools gather and process data from an extensive array of sources, including legacy equipment, resulting in significant issues in terms of communication technologies [61]. Third, the sophistication required for high-end AI applications needs high computing power. Even with recent advancements in microcontrollers/microprocessors and decreasing computational costs, this remains a considerable barrier to the actual development of AI solutions [45].

Against the promise and current challenges of AI, several policy efforts aim at closing the gap between potential and reality (e.g., [62]). Relevant examples include the European Union, which plans annual investments of about €1 billion through the Horizon Europe and Digital Europe programs, plus another €134 billion from the Recovery and Resilience Facility earmarked for digital initiatives [63]; the U.S. government's effort of $3 billion in 2024 [64]; China's New Generation AI Development Plan [65], which aims to build indigenous capabilities and encourage its technology companies to expand abroad; and Japan's outlay of about $1.5 billion to promote advances in generative AI and the creation of supercomputers [66]. Similarly, private investments are steadily increasing [67]. These include foundational models, edge AI applications, automation, and smart functionalities. Involved firms are large software houses and technology giants as well as fast-growing startups.

Alongside actions generally meant to increase the viability of AI, it is important to acknowledge that different contexts have their own specificities in the journey toward the productive adoption of AI. In this respect, the literature on GPTs highlights the presence of positive feedback loops between improvement in core technologies and complementary innovation in application sectors; however, these dynamics have mostly been observed in the consumer sector, where large innovators in the Internet industry have led the development of actual applications and captured related value [21], [10]. Research on innovation dynamics is nevertheless still scant, especially when considering technologies for the industrial space [52].

2.2. AI for climate change in manufacturing

Among the several potential transformative impacts of AI, there are growing expectations around its role in mitigating the impact of human activities on climate change [6], [48]. Academic literature, industry reports, and policy documents highlight a variety of areas: promoting informed decision-making in environmental-social-governance (ESG) investments, leveraging satellite images for environmental surveillance, tracking crop health to reduce pesticide usage, resorting to predictive models to prevent deforestation and promote biodiversity conservation, enhancing renewable energy production and grid management, allowing energy-efficient building design and retrofitting while also controlling their heating systems, forecasting vehicle emissions and optimizing transportation, and improving carbon sequestration and storage processes [7], [13], [68], [69].

When considering manufacturing, AI technology has been related to a reduction in the environmental footprint of internal and supply chain (SC) operations. Within production plants, AI can optimize the use of resources and energy, for example through intelligent control of machine operating parameters [70], [71]. Moreover, intelligent systems enhance operational oversight, enabling the introduction of practices such as real-time monitoring and predictive maintenance that might extend the lifespan of machinery and reduce the need for new equipment [72]. At the SC level, AI can support alignment and control beyond first-tier relationships, thanks to predictive models and integration with diverse sources of information [73]. Data-driven systems might optimize inventory levels and minimize excess production, thus avoiding unnecessary resource utilization [6], [74]. AI is also seen as an enabler of material recycling and circular loops, especially considering solutions for green product design that facilitate end-of-life handling [61]. Lastly, AI may support companies' adaptation to new climate-related challenges, for example by predicting possible SC disruptions due to extreme events and promoting autonomous adjustments [75].

So far, evidence from adopting AI solutions in manufacturing operations and SC activities mostly testifies to a positive impact on sustainability. Case studies show that AI can optimize energy consumption and reduce defects during production, thus driving savings and reducing the environmental footprint [76], [77], [78]. At the SC level, some surveys have shown that the technology might improve sustainability through process flexibility and the circular economy [79], [80], [81]. However, other studies have found AI not to be related to a higher adoption of sustainable manufacturing practices [82] and contest that there is a still too low penetration of AI to draw conclusions [83]. Further, the literature indicates that AI can deliver positive impacts if adopted together with complementary technologies for digital transformation in manufacturing operations and beyond (e.g., the Internet of Things and advanced robotics, electric vehicles, renewable energy technologies – [49], [84], [85]). On balance, it seems increasingly important to overcome techno-optimism when considering the potential of AI for climate change in manufacturing.

As testified by recent discussions at the 28th Conference of the Parties to the United Nations Framework Convention on Climate Change (COP 28, November–December 2023) [86], the development of AI solutions for climate change entails significant challenges on top of those generally related to the technology itself. These are essentially connected with the time and scope of action. On the one hand, the current decade is seen as crucial to keeping the climate at bay, so that there is an unprecedented urgency around the development of viable technologies (e.g., [18], [87]). On the other hand, the complexities of the issues to be tackled require broad cross-sectoral collaborations and the integration of diverse expertise across the technological, business, and environmental domains [88]. This not only implies the need to mobilize consistent financial resources and engage specialist knowledge but also calls for transparency on progress and results [89]. Moreover, it is important to consider tradeoffs, which include energy requirements, infrastructural upgrading, and the risk of augmenting the penalties for those areas in the world that, while lagging behind in terms of digitalization, are also the most affected by current alterations in climate patterns [90], [91].

Whereas the potential and challenges of developing AI for climate change are starting to attract academic interest in prominent managerial outlets (e.g., [11], [58], [92]), there are still few studies that provide evidence-based considerations. Specifically, several articles concern technical applications and decision-making tools (e.g., [93], [94); however, research has still not investigated some core questions that would support managers and policymakers to delineate plans to address the aforementioned challenges. Among these questions, the lack of a clear picture of the current and likely evolution of the AI innovation landscape in manufacturing where climate change is concerned is a major research gap that needs to be tackled given the array of stakeholders involved, each playing a different role in this initial deployment phase, and the level of uncertainty that characterizes the technology at this stage. Theoretically, such an effort can illuminate the interplay between a technology commonly recognized as a GPT and a specific context in terms of application sector (manufacturing) and scope (climate change). There is indeed a need to clarify the unfolding of digital

GPTs when innovation loops involve hardware technologies, as is the case with manufacturing, insofar as AI expands toward broad-range applications [21]. The presence of a specific problem potentially stimulating technological innovation constitutes a further element of interest [95], [96].

3. Methodology

A patent analysis was conducted to provide a systematic overview of the current state and evolutionary trends concerning the development of AI solutions for climate change mitigation and adaptation in manufacturing. Patents serve as a comprehensive repository of knowledge, containing not only the specifics and characteristics of inventions but also relevant information about inventors, applicants, filing dates, and geographic origin [16], [97]. This makes them particularly helpful in understanding the development status at different levels, from individual organizations to industries and economies at large [14]. Patent analysis illuminates trends and facilitates the understanding of how different technologies converge and evolve [39]. Moreover, it can assist in decision-making processes, particularly in the realms of R&D planning and innovation policies [32].

Even though as a software innovation AI might be less apt to be patented and subject to open-source development efforts, prior patent analyses in the context of AI testify to the suitability of this approach [38], [98], [99]. This is motivated by a different attitude toward the protection of software innovation since the early 2000s. Indeed, there has been a rising awareness of the pivotal role that patents play in improving a company's market value [100]; firms now consider patents as an essential part of their business strategies and use them both as defensive instruments and as negotiation tools. Overall, patenting inventions has become a fairly common practice for companies, regardless of the domain [101]. With respect to AI, there have been significant regulatory efforts to establish strong protection of AI-related intellectual property (IP) rights, which is seen as a precondition to boosting investments in the field [102]. Moreover, patenting software innovation is historically a common practice for manufacturing-related applications [103], [104].

When developing a large-scale patent analysis, there are several challenges to consider that are inherent to their nature as legal documents. Advanced methods such as machine learning, data mining, and statistical analysis are used to extract and interpret the dense and complex knowledge they contain, sifting through the vast amounts of raw data to gather meaningful insights. Our study follows the example and methodological guidelines of prior research (e.g., [14], [17], [32], [105], [106],

[107]). The approach, which is based on different techniques, is outlined in Fig. 1 and illustrated in greater detail in the following paragraphs.

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3.1. Data collection

We started our data collection process with the ***database selection.*** Patent information was obtained from "The Lens" (https://www.lens.org/). This is a freely available platform covering all major patent offices worldwide [108], [109] and has been widely used in previous research (e.g., [110], [111]).

In terms of ***search string formulation and time span definition***, our search strategy included both keywords and technology codes [22]. For AI, we followed the recommendations of the World Intellectual Property Organization (WIPO) [112], which provides comprehensive guidelines (i.e., a list of keywords and technology codes) for identifying AI-related innovations and thereby facilitates the selection of relevant technological classes and terms. Specifically, the WIPO [112] guidelines are designed to achieve a tradeoff between precision and recall. In this perspective, they include the following AI techniques: logic programming, fuzzy logic, probabilistic reasoning, ontology engineering, machine learning, and search methods. Functional applications such as large language modeling (LLM) and generative AI are also encompassed.

For the sustainability component, we relied on the recommendations of the Organization for Economic Cooperation and Development (OECD) [113], [114]. The OECD framework classifies patents related to "mitigation or adaptation against climate change" by field of application [115]; given our focus on manufacturing, we selected those related to the "production or processing of goods". With this approach, we did not set any boundaries and considered the whole manufacturing industry (NACE codes 10–33).

The two parts of the resulting query were combined using the "AND" operator (see [112], [113] for the complete list of keywords and technology codes). The search targeted patents granted from 2011 to November 2023 (the date the search was conducted). The starting year is justified taking into account the emergence of digitalization and related concepts [36], [42]. To avoid double counting, patents were considered at the family level [32].

To conclude, the following ***screening process*** was performed. The abstract of each patent was independently reviewed by two authors to ensure consistency with our study objectives (e.g., we removed some patents related to drug development, animal breeding, and agriculture). In cases where there was further uncertainty (e.g., regarding the adopted AI technique), the full text of the patent was considered and an external expert (a researcher in the field of computer sciences specialized in AI) was also involved. This process resulted in the identification of 5,919 patents (i.e., the population of patents related to the use of AI in manufacturing to address climate change issues).

3.2. Analyzing the current state (RQ1)

To shed light on characteristics of the innovation landscape with respect to AI applications for climate change mitigation and adaptation in manufacturing, the following analyses were conducted.

First, we ran some ***descriptive statistics*** aimed at providing an overview of the topic. In line with previous contributions (e.g., [17], [16], [31]), we considered the following variables (see Table AI in the Online Appendix for more details): annual number of patents granted and growth rate, number of patents by priority country, number of patents related to the top 20 applicants and average family size, and number of patents related to the top 20 technologies (IPC codes). Moreover, we also provided information on the top 20 technologies (IPC codes) employed by the top 20 applicants (e.g., [17]).

Second, we performed a ***topic modeling*** analysis to identify the main application domains of AI solutions for climate change mitigation and adaptation in manufacturing. Specifically, we analyzed the collected patents by deploying the latent Dirichlet allocation (LDA) technique (i.e., an unsupervised machine learning approach) [18], [105], [116], [117]. The core concept of LDA is that documents consist of a mixture of underlying topics, where each topic is defined by a specific probability distribution of words. LDA enables the discovery of these hidden structures by analyzing the co-occurrence and frequency of words, thereby categorizing documents according to the latent thematic patterns embedded in the text (see [18], [105], [116] for more details). Previous usage of LDA to identify patent application domains can be found, among others, in Ghaffari et al. [105], Kang et al. [18], and Hu et al. [118]. LDA was performed on abstracts, as they provide information on the main technical content and application domain [105], [118], [119].

A major challenge in performing LDA is text cleaning [120]. The texts of the abstracts should be transformed into homogeneous meaningful words whose repetition and aggregation indicate a domain of application. The cleaning process involved several steps [105], [121]: tokenization, lemmatization, removal of high-frequency stop words, conversion of uppercase letters to lowercase, conversion of numbers to letters, and removal of special characters such as punctuation. In addition, custom stop words that appeared frequently in our patents but did not have a specific meaning were removed (e.g., “first”, “second”, “third”, “method”, “system”, “application”, “unit”, “input”, “embodiment”, “technology”, “apparatus”, “device”, “invention”, “target”, “algorithm”, “data”) [122], [123].

To select the appropriate number of topics, we explored a range from 2 to 15 and considered the coherence score (i.e., a measure that reflects the quality of the analysis by comparing the semantic similarity between highly repetitive words in a topic – [105], [124]). The highest coherence score was 0.58 and was obtained with 6 topics; this value is in line with similar studies (e.g., [105]). Each patent was assigned to the topic with the highest calculated probability using topic distribution. Additionally, the most frequent words in each topic were printed to facilitate interpretation and understanding of the results. The entire process was conducted using Python 3.12.0 software. In line with Ghaffari et al. [105], the LDA was implemented by Gensim library with the following values: random state = 100 to ensure reproducibility of the results, chunk-size = 1000 to control for the number of documents processed at a time, and passes = 70 to define the number of iterations over the entire corpus. The alpha and eta parameters were set to “auto” to allow the model to optimize them during training [125], [126]). The robustness of the results was confirmed by experimenting with different parameter values; these variations yielded consistent and stable topics, demonstrating the reliability of the chosen approach.

To conclude, in line with Su et al. [32], Lee et al. [127], Son and Cho [128], and Block and Song [39], the ***IPC network analysis*** was carried out to reveal the different technologies underlying each topic. The approach allowed us to identify the defining features of our network models, determine technology convergence, and observe the structural characteristics of innovation in the domain [32], [128], [129], [130]. The network analysis was performed on the IPC codes of the patents belonging to the six domains identified with the topic modeling. We constructed a two-dimensional matrix containing all patents and their IPCs. This was transformed into a one-dimensional IPC x IPC matrix, which was then converted into a network. Gephi 0.10.1 software was used to draw the network diagram, with each node representing a technology area (IPC code) and the (undirected) edges indicating whether a patent exists between nodes (IPC codes) “A” and “B”. On these data, the following indicators were used (e.g., [32], [105], [107], [131], [132]): *degree centrality*, which indicates the importance and influence of the technology (node) in the network; *betweenness* *centrality*, which expresses whether a node occupies a structurally central position in the network (i.e., is a bridge in the network); and *graph density*, which measures how connected the graph is.

3.3. Examining time evolution and forecasting future trends (RQ2)

To analyze development trends of AI solutions for climate change mitigation and adaptation in manufacturing, we first reiterated the ***IPC network analysis*** for two time intervals to examine the past evolution of technologies underlying each topic**.**

Then, we performed a ***growth trend and forecasting*** analysis of the number of patents for each of the six domains; previous adoption of this approach can be found, among others in Jiang et al. [14], Su et al. [32], Coccia and Roshani [133]. We began from the widely accepted premise that a technology life cycle typically takes the form of an S-shaped curve with four stages, namely birth, growth, maturity, and saturation [32], [133], [134], [135]. The most used models to describe this S-shaped pattern are the Logistic, Gompertz, and Richards ones (e.g., [14], [136], [137]). The logistic model is renowned for its simplicity and effectiveness. The Gompertz model is often preferred for its accuracy in capturing the early stages of growth, particularly in cases with a slow initial uptake and rapid later growth. The Richards model is an extension of the Logistic one and allows for greater flexibility in representing the growth curve, making it suitable for a wider range of technology adoption patterns (see [14], [32], [134], [137], [138] for a detailed description of these models).

We considered the cumulative number of patents and analyzed the data by dividing the period into six-month intervals [32]. Since data collection was conducted in November 2023, we used data up to the first half of 2023. Consistent with Jiang et al. [14], we applied the logistic, Gompertz, and Richards models using the Loglet 4 software. For the Logistic and Gompertz models, this tool considers three parameters: *saturation* (the estimated maximum number of patents filed over time), *growth time* (the time taken for the technology to pass through the growth stage and reach maturity), and the *midpoint* (the exact point at which the growth trend enters the maturity stage). For the Richards model, a fourth parameter is added: the *shape* (which accounts for the curvature of the growth model) [139]. These parameters were estimated using a Monte Carlo annealing over a genetic algorithm.

As stated before, each model has distinct characteristics and is better suited to capturing different growth patterns and stages of technology development [14], [133], [137]. To select the model that best fits each case, we considered the values of mean absolute percentage error (MAPE) and R^2 [32]. In cases where there were discrepancies between these two measures, we preferred the model with the best MAPE value rather than R^2. This is because while R^2 refers to the explanatory power of the model, MAPE focuses on forecast error, making it more meaningful for our purposes [140].

4. Results

4.1. The current state of AI for climate change in manufacturing (RQ1)

Starting with the ***descriptive statistics****,* Fig. 2 shows a clear upward trend in the annual number of patents related to AI solutions to address climate change in manufacturing. The average number is still low until 2021 (98.36 yearly), sharply increasing in 2022 and 2023 (until November, with a growth rate of 119.70% since the previous year). This rise can be attributed to three main factors. First, as is common for GPTs, AI is characterized by increasing maturity and applicability [9], [44]. Second, the related technology stack is also rapidly evolving, so that there has been a remarkable growth in computing power and data processing capabilities, which has expanded the development of solutions [21], [71]. Third, there are growing institutional pressures to invest in green technologies, which also direct private efforts in the field of AI [141].

————————INSERT FIG. 2 APPROXIMATELY HERE————————

In terms of geographical distribution (Fig. 3), 78% (4,629) of patents originate from China, followed far behind by the United States (10%, 603), South Korea (5%, 286), and Japan (4%, 218). This trend is clearly correlated with the fact that since the early 2010s Chinese policies incentivize organizations that demonstrate technological innovation through patent filings [142].

————————INSERT FIG. 3 APPROXIMATELY HERE————————

Consequently, Table I shows the dominance of Chinese applicant organizations, particularly universities. This also reflects the country's strategic efforts to foster innovation through public funding [143]. In contrast, the landscape in the United States, and to some extent in Europe, leans heavily on major corporate players such as IBM, Rockwell Automation, and Siemens. These companies are representative of a model of innovation driven by industry and technology giants [144], [145]. Interestingly, US players such as Google, Amazon, and Microsoft, despite their prominence in general AI development [146], [147], [148], seem not to have invested in AI applications that are specifically devoted to addressing climate change in manufacturing. This is an intriguing aspect, especially when considering their expansive reach and influence in broader technological contexts. Moreover, the "Average family size"[1] metric unveils the breadth of patenting efforts [149].

[1]A patent family includes all the patents filed across different countries that are related to the same invention. Thus, the family size serves as an indicator of the geographical breadth of a patent applicant's filing strategy [152].

Applicants with larger family sizes (e.g., Fanuc and Siemens) pursue an extensive international reach in their filing strategy, contrasting with the more localized focus of Chinese universities. This diversity can be indicative of a more varied innovation portfolio and points to different approaches in protecting intellectual property [17].

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Table II outlines the top 20 IPC codes along with their descriptions. The most important are related to Computational models (G06N) and Electric digital data processing (G06F). These categories represent the core capabilities of AI [150], [151]. Other IPC codes reflect a more specific focus, such as visualization technologies (Image or video recognition–G06V and Image data processing–G06T) or process automation (Control or regulating systems–G05B). Lastly, the presence of Manipulators (B25J) signals advancements in robotic systems. This is in line with the literature showing a significant use of AI together with advanced automating solutions [153], [154], [155].

————————INSERT TABLE II APPROXIMATELY HERE————————

Table III shows the top 20 technologies (IPC codes) employed by the top 20 applicants. There is a mix of generalist players, organizations with targeted expertise, and companies with both general AI capabilities and specific knowledge. Each applicant tailors its approach either to particular aspects or to broad AI integration [17]. The Guangdong University of Technology, for instance, focuses on core AI computational models and data processing techniques (Computing arrangements–G06N and Digital data processing–G06F). Fanuc's investment in Manipulators (B25J) highlights a specialization in robotics. Baidu covers areas such as ICT for administrative purposes (G06Q) and Image or video recognition (G06V), suggesting a versatile application of AI across different aspects. Universities such as Zhejiang University and South China University of Technology indicate a strong inclination to develop solutions for material testing and quality assurance (Material analysis–G01N). IBM, with investments in categories such as Digital data processing (G06F) and Control or regulating systems in general (G05B), integrates AI into a wide array of applications from core computing to specialized control systems.

————————INSERT TABLE III APPROXIMATELY HERE————————

The outcomes of the ***topic modeling*** analysis are presented in Table IV alongside the defining keywords emerging from the data analysis. The six categories reflect different fields of application within manufacturing. Finally, the ***IPC network analysis*** shows the technologies underlying the six application domains of AI by analyzing the IPC codes behind each patent. The results for each domain are reported in Table V and graphically represented in Fig. A1 (Online Appendix). In the following paragraphs, the findings are briefly commented for each field of application.

————————INSERT TABLE IV APPROXIMATELY HERE————————

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(1) *Predictive analytics (1,434 patents – 24.23%)*: This topic underlines the key role of AI in tasks related to predictive maintenance and the control of process parameters. The patents underscore AI's capability to analyze large amounts of data in real-time, enabling organizations to improve maintenance periods and anticipate equipment failures, significantly reducing unplanned downtime and extending machinery lifespans. These aspects lead to a decrease in energy consumption (idle time), water usage (equipment cooling and washing), and machine substitution rates. Furthermore, included patents show opportunities for fine-tuning manufacturing processes to their most efficient settings, eliminating unnecessary power peaks and overproduction.

    Within this domain, the top five IPC codes by **degree centrality** (Programme-control systems–G05B19, Computer systems based on biological models–G06N3, ICT specially adapted for implementation of business processes of specific business sectors–G06Q50, ICT for Administration; Management–G06Q10, and Machine learning–G06N20) highlight a focus on modeling, data governance, and responsiveness, as well as the need to tailor analytics capabilities to context-specific requirements. The results also show an overlap in IPC codes between degree and **betweenness centrality**, suggesting their function as both enablers and links of different technological aspects in the domain. The presence of Adaptive control systems (G05B13) in the betweenness metric draws attention to the need to integrate various functionalities. The **number of IPCs** (i.e., nodes) (520) indicates a domain characterized by a wide range of technologies, whereas **graph density** (0.026) depicts a rather sparse network, suggesting the presence of many applications tailored to specific use cases.

(2) *Material sorting (1,195 patents – 20.19%)*: This topic concerns material identification and selection. AI-driven sorting systems can distinguish and accurately classify substances and components. The patents concern AI applications to correctly identify and use materials when/where they are most needed, while avoiding waste and scrap due to undetected problems with the initial inputs. AI applications also facilitate the incorporation of recycled materials into production processes.

Within this domain, the top five IPC codes by **degree centrality** (Computer systems based on biological models–G06N3, Arrangements for image or video recognition or understanding–G06V10, Image analysis–G06T7, Programme-control systems–G05B19, and Scenes; Scene-specific elements–G06V20) highlight a core of complex modeling technologies and visual data processing/analysis. These IPC codes also rank among the top five for **betweenness centrality**, showing their relevance for the alignment of various image management and categorization capabilities. The total **number of IPCs** (307) and the **graph density** (0.038) show a domain with a diverse set of technologies that interconnect in a relatively sparse network, pointing to applications tailored to specific types of materials or tasks.

(3) *Defect detection (1,107 patents – 18.07%)*: This domain underscores the role of AI in identifying quality issues, detecting a wide range of defects from surface anomalies to structural inconsistencies. This can reduce the number of discarded items and facilitate the proactive identification of quality issues, significantly minimizing the environmental impact associated with withdrawing goods at a later stage.

Here, the top five IPC codes by **degree centrality** (Computer systems based on biological models–G06N3, Image analysis–G06T7, Arrangements for image or video recognition or understanding–G06V10, Machine learning–G06N20, and Methods or arrangements for reading or recognizing printed or written characters or for recognizing patterns–G06K9) show the integration of modeling, surface analysis, and visual inspection technologies, enhanced by the capability to compare reality with established data formats and structures. Also in this case, the overlap of codes between degree and **betweenness centrality** showcases their significance as core technologies within this domain while also integrating the diverse capabilities required for defect detection. The high value of betweenness centrality for Pattern-recognition (G06F18) underscores the relevance of technological capabilities to synthesize diverse data types and sources. By the **number of IPCs** (181), this domain appears to be characterized by a specialized concentration of technology areas. **Graph density** (0.063) indicates a denser network compared to other domains, reflecting the closer interconnection of technologies and core systems.

(4) *Advanced robotics (880 patents – 14.87%)*: This topic shows how AI can enhance robotic capabilities, enabling the execution of complex tasks. This leads to a dual benefit: first, it

reduces the production of off-specification goods, cutting down on material wastage and consumption associated with rework. Second, it minimizes stress on the machine itself, thus mitigating wear and extending the equipment's lifespan. Another implication stems from their adaptability, allowing companies to produce according to demand. When considering material handling and logistics, AI-enabled robotics streamline movement through smart routing, cutting down on the energy consumed.

In this domain, the top five IPC codes by **degree centrality** (Control of position, course, altitude, or attitude of land, water, air, or space vehicles–G05D1, Programme-control systems–G05B19, Programme-controlled manipulators–B25J9, Navigation; Navigational instruments not provided for in groups– G01C21, and Traffic control systems for road vehicles–G08G1) combine elements of motion control and environmental awareness, which are required for robots to perform assigned tasks while also taking into account the conditions of the operating context. Among the codes with the highest **betweenness centrality**, the presence of Computer systems based on biological models (G06N3) and Speech recognition (G10L15) suggests that the nature of robotics operations demands the gathering and interpretation of data from several sources. The domain presents an intermediate **number of IPCs** (357) connected in a relatively sparse network, with a **graph density** of 0.044. This indicates a balance between the breadth and depth of technology development across different activities.

(5) Scheduling (768 patents – 12.98%): This topic reflects AI applications for synchronizing activities considering real-time parameters. This reduces the risk of producing more than necessary and improves load leveling across the shop floor, yielding reductions in bottlenecks and idle times with consequences on power consumption.

Here, the top five IPC codes by **degree centrality** (Computer systems based on biological models–G06N3, Administration; Management–G06Q10, Systems or methods specially adapted for a specific business sector–G06Q50, Computer-aided design–G06F30, and Programme-control systems– G05B19) underscore the reliance on advanced computational techniques and data processing that need to be adapted to specific contexts. The consistency of codes with **betweenness centrality** provides further evidence of the key role of these IPCs in facilitating the convergence of different scheduling functions. The **number of IPCs** (163) shows that the domain is dependent on a limited number of specific technologies, whereas an intermediate value of **graph density** (0.055) reveals a moderate level of interconnection.

(6) *Resource optimization (535 patents – 9.04%)*: This domain covers AI's applications for energy efficiency and resource management. Central to this domain is the ability to analyze and predict energy patterns, ensuring that energy-intensive tasks coincide with periods of high availability of renewable sources. In addition, applications extend to the management of complex systems such as central air conditioning to maximize energy efficiency. AI is also useful in identifying the most effective wastewater processing parameters, allowing for water purification and reuse.

In this domain, the top five IPC codes by **degree centrality** (Computer systems based on biological models–G06N3, Systems or methods specially adapted for a specific business sector–G06Q50, Administration; Management–G06Q10, Programme-control systems–G05B19, and Circuit arrangements for ac mains or ac distribution networks–H02J3) show the need to develop solutions tailored to specific business needs. Moreover, the presence of codes related to electrical power control highlights the critical role of energy management solutions. While computational models and application-specific approaches emerge as top nodes in both degree and **betweenness centrality**, the presence of Investigating or analyzing materials by specific methods (G01N33) testifies to the relevance of material (e.g., water, gas, air, chemical substances) analysis capabilities. For what concerns the **number of IPCs** (292), the domain occupies an intermediate position in terms of technological diversity. These technologies are not extensively interconnected, as evidenced by the **graph density** (0.039).

To summarize, the potential impact of AI manufacturing applications for climate change concerns developments to reduce material usage, enable material recycling, reduce energy consumption, reduce water consumption, and enable the use of renewable energy. Some impacts are specific to certain domains. With respect to the number of patents, *(1) Predictive analytics* and *(2) Material sorting* show the highest number of filings. The figure is lower for *(5) Scheduling* and *(6) Resource optimization*. This might be related to the market demand for such inventions [156], [157]. In the realm of sustainability, extant research shows that companies prefer solutions that not only strengthen environmental performance but also generate cost savings and efficiencies [158], [159]. Customer demands have likely guided the innovation endeavors of technology developers, leading them to focus their resources and efforts on domains with the highest attractiveness to the users [95], [96]. Finally, with respect to the outcomes of the IPC network analysis, alongside specific technologies, the results highlight the essential role of core technologies, such as Computer systems based on biological models and Machine learning. These serve as the backbone of AI applications, allowing for real-time or close to real-time data gathering, processing, and analysis. In this respect, there is evidence of interdependent innovation occurring between a main technology stack and domain-specific technological applications, which is in line with evolutionary trajectories common for GPTs [20], [22]. The role of AI in stimulating innovation in other areas—such as robotics—is also evident and underscores its contribution to improving technologies for climate change [22].

4.2. The evolution of AI for climate change in manufacturing (RQ2)

The ***IPC network analysis*** for time intervals (Table VI) considered two periods (2011–2021 and 2022–2023) in line with the trend related to the annual number of patents (Fig. 2). The analysis shows that the relevance of many IPC codes remains unchanged, while their degree and betweenness centrality values are generally increasing. The only exception is in *(4) Advanced robotics*, where both the degree and betweenness values of the top nodes tend to decrease. This suggests weakening connections within the domain, possibly due to a shift toward a broader range of applications. Regarding network density, it is observed that it generally decreases over time. This indicates that while the number of technologies is growing, their interconnections are becoming sparser, reflecting a trend toward more specialized developments in manufacturing.

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Concerning ***growth trend and forecasting***, the Logistic, Gompertz, and Richards models were used to understand the development trends of the six AI application domains [14], [137]. Each model has its own unique features, making it particularly effective at describing specific development patterns. For each domain, we therefore considered the forecasts of the model that best suits the data (taking into account the values of MAPE and R^2).

The results (Table VII) show that the Richards model performs better in describing the current and future diffusion trends of Predictive analytics, Defect detection, Scheduling, and Resource optimization (lowest MAPE and highest R^2), while the Gompertz model fits better for Material sorting and Advanced robotics (lowest MAPE). Moreover, the values of R^2 and MAPE are in line with previous studies (e.g., [14], [32], [138]); according to the Lewis scale [160], MAPE data depict a good/reasonable prediction. Table VII also shows that the F-tests for the considered models are all statistically significant, with p-values < 0.05. This further demonstrates that they are a good fit for describing AI-related patenting activity [41], [133]. The trends are graphically illustrated in Fig. 4. All domains are in the growth phase, with a current saturation level of approximately 30%. The projected saturation points—ranging from 2025 for *(3) Defect detection* to 2037 for *(4) Advanced robotics*—reveal a staggered progression toward technological maturity; while some seem to be rapidly approaching saturation, others are characterized by slower trajectories and a possible different focus in the coming years. These slightly different trajectories can be explained by the fact that the fast-moving domains could benefit from a synergy of more mature technological foundations, established R&D efforts, and robust market demand (e.g., [156], [161], [162]). On the other hand, domains with more gradual progress indicate underlying complexities [163], [164]. For instance, due to software and hardware interdependencies, several innovation feedback loops are needed before AI can be applied to more sophisticated automation processes, so that *(4) Advanced robotics* might capitalize on these advances only at a later stage. This sequence reflects a natural progression in technological evolution, where the growing maturity of data analysis and decision-making solutions precedes and potentially catalyzes the subsequent development of innovation in automation [16], [165].

————————INSERT FIG. 4 APPROXIMATELY HERE————————

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5. Discussion

The aim of this study was to provide a systematic analysis of real-world trends concerning the development of AI solutions for climate change mitigation and adaptation in manufacturing. In this section, we present the key messages emerging from our findings and discuss them against prior literature. In Fig. 5, we provide a summary framework building on the results of topic modeling, IPC network analysis, and future trend prediction. Starting from a set of core IPC codes that constitute the basis of AI, these are combined with specialized technologies in order to apply AI to six different domains of manufacturing. Except for *(6) Resource optimization*, each application domain is characterized by primary operational impacts (i.e., cost, quality, time, flexibility), which impact only indirectly objectives related to mitigating the impact of manufacturing on the environment (e.g., reduce material usage, enable material recycling). In *(6) Resource optimization*, instead, it appears that growing pressures toward recycling and using renewable sources are fostering the development of AI solutions, allowing more cost-efficient processes. It also appears that most patenting efforts so far have focused on applications to increase manufacturing sustainability, rather than AI solutions for climate adaptation. This result is in line with prior studies on AI innovation for climate change and reflects most of the current views on AI in manufacturing [22], [166], [167]. Although all six AI application domains are currently in the growth phase, they are characterized by different paths toward saturation.

————————INSERT FIG. 5 APPROXIMATELY HERE————————

Looking at our findings through the lens of GPT, some considerations emerge from our analysis. First, *the development of AI solutions to address climate change in manufacturing requires core and specialized efforts*. The results show the importance of integrating the development of AI at various levels, building on core technologies to advance with specialized solutions concerning single application domains (Section 4.1). This integration is critical considering the complex requirements of manufacturing and the parallel evolutions of related hardware and software technologies [16], [37], [97] and seems coherent with the concept of GPT loops (i.e., feedback loops developed through co-invention determining innovation in both core technology and application sectors) [21]. Similarly, our results show that AI is indeed formed by a technology stack involving a number of AI-related GPTs (as shown by the presence of multiple IPCs among core technologies in Fig. 5). The interplay between AI innovation pathways and those of other technologies related to digital transformation in manufacturing (e.g., advanced robotics) and climate tech solutions (e.g., energy management) is also emerging from our analysis. This dynamic goes beyond the conventional understanding of GPT-related innovation complementarities [20], [53]: when considering AI for climate change, our findings show that complementarities not only involve downstream application sectors but also other major technological fields related to automation/digitalization and decarbonization that might display features of GPTs [22].

Second, *the development of AI for climate change in manufacturing presents various and interdependent evolutionary trends*. Looking backward, the analysis underlines a growing number of technologies whereby interconnections are becoming sparser, suggesting increasing specialization. The forecasts proposed by the Gompertz and Richards curves for the six AI application domains show different maturation timelines (Section 4.2), ranging from the imminent saturation of defect detection (2025) to the later development of advanced robotics (2037). Moreover, it is relevant to note that advancements in some domains and core technologies (i.e., those related to data processing and analytics) appear as a precondition for the development of more advanced solutions in other domains (i.e., automation for *Advanced robotics*). This again underlines the interplay of innovation loops between a GPT core technology stack and application domains [21], indicating, moreover, evolutionary trajectories that are specific to clusters of applications within a sector.

Third, *operational performance and climate change mitigation/adaptation are intertwined objectives when developing AI for manufacturing applications***.** The topic modeling analysis (Section 4.1) depicts a context in which the prevalence of patents for specific domains reflects market demands for solutions that ensure higher operational performance. Domains such as *Predictive analytics*, *Material sorting*, and *Advanced robotics* are widely recognized for their role in enhancing operational efficiency [168], [169], rather than for their contribution to environmental sustainability. In other words, AI is mainly used for productivity and process improvement, with the increase in sustainable manufacturing performance emerging only as a secondary effect. As far as *Resource optimization* is concerned, against growing requirements for responsible use of natural resources and trends toward circularity of materials, manufacturers need cost-effective approaches that can be enabled by AI [170]. Overall, these results confirm the role of market dynamics in directing the course of technological progress for meeting sustainability goals. In this perspective, it is interesting to note that, even though the patents were specifically selected to identify AI developments for "mitigation or adaptation against climate change" (see Section 3), the solutions appear related to domains traditionally rooted in fostering manufacturing productivity and operational effectiveness [168], [169]. The impact of these technologies on reducing the environmental footprint of manufacturers, although extensive and relevant (as described above), appears to be more of an indirect or complementary benefit. This may suggest that the primary motivation for developing and adopting AI-driven tools is to enhance operational performance, with sustainability gains emerging from higher efficiency. These trends seem consistent with dynamics already expounded in the literature when considering problem-driven innovation, as the unfolding of consequential problems and their solutions induce the emergence and development of innovation [96]. In this sense, it can be argued that AI's role in promoting environmental sustainability might become more prominent as a consequence of regulatory pressures, stakeholder demands, and societal expectations [171], [172]. Future developments are likely to embed from the outset aspects such as consumption optimization and pollution reduction, representing a major shift from actual practices. This anticipated evolution might mark a significant step forward in aligning the capabilities of AI with the urgent need for climate change mitigation and environmental protection [86].

Finally, *only a minority of organizations have adopted a comprehensive strategy that integrates the development of both core and specialized AI solutions*. When considering the focus of the top applicants (Table III), most players are focused on specific technologies (i.e., IPC codes). These results show a peculiarity in the manufacturing industry as opposed to the consumer sector, which appears instead dominated by tech giants in the development and commercialization of AI [10]. Given the interplay between core and specific AI technologies, the analysis shows that innovators might avoid establishing a full range of AI capabilities internally by pursuing strategic alliances and partnerships with organizations that possess complementary characteristics [173], [174]. The challenges of this path relate to goal alignment, intellectual property concerns, and the need to establish effective collaboration mechanisms [175].

In addition to these insights, one important message stems from the geographical distribution of AI patents (Fig. 3, Table I) that underlines the dominance of China against rooted technology giants such as the United States and Japan [101]. This highlights a significant shift in the epicenter of innovation and points to the global nature of the "AI race": the traditional model seen in technologies and paradigms such as the Internet of Things and Industry 4.0 [16], [37], where inventions come from a few highly developed countries, is now being challenged. In this perspective, the leading role of China's public universities confirms strong governmental support for innovation [143]. By sustaining public institutions for AI research, the state administration ensures that technological progress not only advances at a rapid pace but also aligns with national priorities and strategic goals, underscoring a deliberate move to shape and direct the course of innovation from the top down [176], [177].

6. Conclusions

This study provides relevant implications for theory, practice, and policy. Starting with the contributions to theory, we answer previous calls for more research on AI and sustainability (e.g., [11], [91]), presenting the first large-scale patent analysis that explores the landscape of AI solutions to address climate change in manufacturing processes. By considering a dataset of 5,919 patents coming from all major patent offices, we move a step forward from conceptual studies and literature reviews, grounding our findings in tangible evidence. Our analysis not only clarifies the actual domains of AI adoption but also depicts the underlying technologies and future trends. Specifically, the findings provide an empirically grounded overview of the innovation trajectories of AI as a GPT, confirming some general dynamics while highlighting specificities in terms of GPT loops and complementarities with clean tech and digital transformation technologies [21], [22].

Another contribution to theory stems from showing that AI innovation seems to be targeted at improving operational performance, with climate change mitigation/adaptation playing the role of a notable but secondary benefit. This challenges the dominant narratives found in the extant literature (e.g., [11], [12], [48]) and underlines the intricate nexus between technological innovation, business performance, and sustainability outcomes. This is also relevant in terms of problem-driven innovation, suggesting the relevance of institutional pressures to stimulate and sustain technological development in this domain.

Lastly, the study has highlighted some differences in terms of players and geographies of AI development: China is mainly committed to fostering innovation through public investment, while the arena in the United States and Europe is often characterized by major corporate entities. This points to relevant considerations in terms of how different innovation ecosystems—state-led versus market-led—affect the pace and nature of technological advancement. Along these lines, we show peculiarities that make AI manufacturing applications different than those developed in the consumer sectors, driving the presence of a diverse set of players [10].

This study also delivers valuable insights to practice. By demonstrating that the role of AI solutions to address climate change in manufacturing processes is primarily focused on six domains—*predictive analytics, material sorting, defect detection, advanced robotics, scheduling,* and *resource optimization*—we hope to offer executives guidance for both the adoption and development of this technology. Firms seeking to improve the environmental dimension of their activities can leverage our findings to gain a comprehensive overview of the AI-enabled approaches available for such a purpose. In parallel, sustainability consultants may find our research relevant in advising companies on the selection of AI-driven strategies that best align with their goals. Taken together, these aspects could foster AI diffusion with potential benefits for society as a whole.

On the development side, a deep dive into the technologies underpinning the six application domains provides a clear understanding of the underlying knowledge and skills necessary to develop and manage AI solutions. By assessing their internal capabilities against these specific requirements, organizations can identify areas where improvements are needed or where external expertise should be sought. This is relevant for guiding strategic decisions on training, R&D efforts, and alliance formation, ensuring that companies and public entities are adequately prepared to innovate and maintain a competitive edge in the AI arena. Along similar lines, the study's projection of future patterns in AI enables strategic foresight into the evolving landscape of sustainable manufacturing. Identifying emerging trends is critical to making informed decisions about innovation paths and resource allocation. By staying attuned to these developments, companies can position themselves to capitalize on new opportunities and technological competitiveness, securing a leading role in the paced world of sustainable manufacturing. Our findings call on organizations to take a dynamic, forward-looking approach to their AI R&D strategies, carefully selecting their interest fields based on both current trends and future prospects. Early investment in rapidly maturing domains could yield immediate benefits, while engagement in domains with longer horizons requires a vision that embraces incremental progress and long-term potential [178], [179]. Effective strategic planning, therefore, requires a judicious balance between capitalizing on near-term advances and nurturing emerging domains that are poised to shape waves of innovation in the years to come. In this perspective, Chinese organizations, which are at the forefront of AI patenting efforts, might find our results valuable for maintaining their advantage and further fostering technological progress. For companies in Europe and the United States, this information could serve as a strategic roadmap.

As for the contributions to policy, the findings suggest that US and European policymakers need to consider the effects of different patenting levels of AI solutions to address climate change in manufacturing. Overall, our findings urge policymakers to reflect upon how to prioritize and measure the effectiveness of incentive schemes and financial support for R&D in AI technologies. This could include tax breaks for organizations investing in AI research, grants for collaborative projects, and increased funding for AI-focused education and training programs, which however should be measured for their efficacy [180]. On the other hand, in China, the significant role of universities in AI patenting underscores the potential of university spin-offs, state-owned enterprises, and public-private ventures to commercialize these solutions. Policies aimed at fostering collaboration with businesses could be key to ensuring a balance between more basic and applied research [17], [181].

Moreover, the presentation of likely future trends might help policymakers and funding agencies to better identify which areas need more support. This information offers valuable insights for making strategic decisions, enabling the direction of resources toward the most promising domains to facilitate technology transfer, stimulate economic growth, and drive social change [132].

This article has some limitations that might be addressed by future studies. First, while the use of patents to analyze innovation dynamics is a well-established approach, it presents some drawbacks. Specifically, not all innovations are captured in patent data, as some may be unpatentable or better protected through other means/approaches (e.g., [16]). Future research could consider additional secondary sources (e.g., industrial and funded projects) [62] or gather primary data by conducting interviews and running surveys with policymakers, technology providers, and users.

Second, while the study used LDA to identify AI application domains building on patent abstracts, it potentially missed relevant information contained in other sections, such as claims and drawings. Future studies could benefit from employing more sophisticated topic modeling techniques and examining the whole body of the documents.

Third, while an assessment of the actual impact (i.e., effectiveness for climate change adaptation/mitigation) of patented AI solutions is beyond the scope of our study, we believe it deserves further investigation.

Fourth, despite the Logistic, Gompertz, and Richards models providing reliable and robust forecasts both in terms of explaining historical trends and predicting the future development of AI solutions to address climate change in manufacturing, they mainly account for endogenous growth factors and overlook exogenous influences that could radically alter future trajectories. A relevant example is quantum computing, as an exogenous paradigm shift in technology [182]. By leveraging quantum mechanics and physics (e.g., [132]), quantum computing is poised to provide exponential computational power, making it a critical driver of future technological advances [183]. In the context of our analysis, it has the potential to accelerate the maturation of existing AI applications and foster the creation of novel solutions [41], thereby transforming the landscape depicted so far [184].

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Table I: Top 20 applicants

Applicant	Country	Type	Number of patents	Average family size
Guangdong University of Technology	China	University	67	2.04
Fanuc	Japan	Company	60	7.07
South China University of Technology	China	University	50	2.04
Zhejiang University	China	University	50	2.38
Baidu	China	Company	47	2.66
Central South University	China	University	41	2.07
Huazhong University of Science and Technology	China	University	41	2.00
Ping An Technology	China	Company	40	2.60
University of Electronic Science and Technology of China	China	University	39	2.00
Northeastern University	United States	University	38	2.68
Rockwell Automation	United States	Company	38	4.84
Beihang University	China	University	37	2.03
Siemens	Germany	Company	36	6.00
Xi'an Jiaotong University	China	University	35	2.09
Chongqing University	China	University	34	2.18
IBM	United States	Company	34	3.82
Tsinghua University	China	University	33	2.39
Beijing University of Science and Technology	China	University	30	2.07
Harbin Institute of Technology	China	University	29	2.17
Hefei University of Technology	China	University	29	2.07
State Grid Corporation of China	China	Company	29	2.41

Table II: Top 20 IPC codes

IPC code	Description	Number
G06N	Computing arrangements based on specific computational models	2709
G06F	Electric digital data processing	2043
G06Q	Information and communication technology specially adapted for administrative purposes	1699
G06V	Image or video recognition or understanding	1202
G06T	Image data processing or generation	1071
G05B	Control or regulating systems in general	834
G06K	Graphical data reading	581
G05D	Systems for controlling or regulating non-electric variables	520
B25J	Manipulators	302
H04L	Transmission of digital information	243
G01N	Investigating or analysing materials by determining their chemical or physical properties	215
G10L	Speech analysis techniques or speech synthesis	184
G16C	Computational chemistry/materials science	109
B33Y	Additive manufacturing	95
B29C	Shaping or joining of plastics	86
H02J	Circuit arrangements or systems for supplying or distributing electric power	78
H04N	Pictorial communication	73
H01M	Processes or means for the direct conversion of chemical energy into electrical energy	72
H01L	Semiconductor devices	64
B65G	Transport or storage devices	62

Table III: Top 20 IPC codes employed by the top 20 applicants

	A61B	B25J	B33Y	G01D	G01M	G01N	G05B	G05D	G06F	G06K	G06N	G06Q	G06T	G06V	G07C	G10L	G16C	G16H	H01L	H02J	H04L	H04N
Guangdong University of Technology	-	-	-	-	-	8	11	1	84	10	143	99	37	46	3	4	3	4	-	-	15	-
Fanuc	-	60	-	-	-	-	123	6	29	11	91	4	12	-	-	7	-	-	-	-	7	6
South China University of Technology	-	31	-	4	-	7	2	2	48	5	100	21	52	69	4	6	-	-	-	2	6	2
Zhejiang University	-	-	-	4	3	-	16	2	84	43	108	61	10	17	17	-	-	-	2	6	-	-
Baidu	-	-	-	-	-	9	-	3	51	5	38	34	30	33	-	13	-	4	-	-	3	8
Central South University	-	-	-	-	3	7	7	-	51	29	90	43	10	30	-	-	9	-	-	-	-	7
Huazhong University of Science and Technology	-	-	-	-	-	10	2	1	41	33	117	81	31	33	-	-	23	-	-	-	-	-
Ping An Technology	2	-	-	-	-	-	-	-	58	-	50	34	16	35	3	14	2	16	-	-	10	3
University of Electronic Science and Technology of China	13	-	-	3	-	9	-	-	25	12	73	26	32	34	-	-	-	5	14	-	-	-
Northeastern University	-	-	-	4	-	4	8	3	48	7	81	58	8	20	-	-	4	-	-	-	-	-
Rockwell Automation	-	-	-	-	-	-	92	5	82	8	52	25	-	4	11	-	-	2	-	8	20	-
Beihang University	2	1	-	4	-	-	2	1	67	10	85	58	25	21	-	-	4	-	-	-	3	-
Siemens	-	8	31	-	-	-	86	5	60	17	70	35	6	-	6	-	-	-	-	8	13	-
Xi'an Jiaotong University	-	2	-	4	9	-	4	6	62	19	72	50	5	18	4	-	5	-	-	3	-	5
Chongqing University	-	-	-	3	5	5	2	1	83	4	70	55	15	14	-	-	-	-	-	-	-	5
IBM	9	3	4	-	-	-	66	9	59	11	57	49	5	8	5	-	-	-	16	7	16	-
Tsinghua University	-	11	6	-	9	9	6	6	35	7	64	17	29	33	-	6	-	-	2	11	4	5
Beijing University of Science and Technology	-	-	-	-	-	-	-	1	58	14	88	45	26	13	-	-	-	-	-	-	10	-
Harbin Institute of Technology	-	6	-	-	4	-	8	6	34	19	22	12	19	21	-	-	-	-	-	-	-	-
Hefei University of Technology	-	2	-	-	-	-	2	2	8	9	64	52	6	4	-	-	4	-	-	-	2	-
State Grid Corporation of China	-	-	-	-	-	-	4	6	54	20	54	73	10	10	-	8	-	-	-	14	-	10

Table IV: Topics with keywords and related names

Topic	Name	Keywords	Patents	Share
1	Predictive analytics	control, signal, configuration, communication, monitor, sensor, status, intelligent, connected, platform	1434	24.23%
2	Material sorting	image, recognition, material, segment, region, part, surface, identification, area, color	1195	20.19%
3	Defect detection	sample, quality, defect, feature, evaluation, test, abnormal, classification, accuracy, standard	1107	18.70%
4	Advanced robotics	robot, position, task, motion, coordinates, track, agv, map, angle, movement	880	14.87%
5	Scheduling	scheduling, time, order, parameter, plan, optimization, cost, production, strategy, requirement	768	12.98%
6	Resource optimization	energy, power, electric, weight, optimization, parameter, variable, state, temperature, dynamic	535	9.04%

G06F18	0.0884	G01C21	101	G06N3	0.0833	G06F30	52	G05B19	0.0973	G05B19	67	G06Q10	0.0804
G06N20	0.0862	G08G1	93	G10L15	0.033	G05B19	50	G06F30	0.0589	H02J3	66	G01N33	0.0619
G06K9	0.066	H04W4	86	G06N20	0.0322	G06N20	44	G06N20	0.0479	G06N20	65	G05B19	0.0602
G06Q50	0.0614	G06Q10	76	G01C21	0.0317	G06F17	40	G05B13	0.046	G06F17	59	B23K26	0.058
G01N21	0.057	G06Q50	70	F01D5	0.0313	G06F16	32	G06F17	0.0308	G05B13	49	G06F30	0.0499
G05B19	0.0421	G06N3	69	G06Q50	0.0241	G05B13	31	G08B21	0.0236	G06F30	47	G05B13	0.0484
G06Q10	0.0418	G06T7	66	G06V10	0.0235	G06Q30	30	G06F16	0.0187	G06F11	45	H02J3	0.048
H01M10	0.0336	B62B5	66	G06Q10	0.0234	G06F11	29	G06F11	0.0153	G06Q30	40	H01M8	0.0427
G06F30	0.0326	H04L29	64	G06T7	0.0225	G06K9	27	G16C20	0.0136	G06F16	39	G06F18	0.0416
H01M4	0.0318	B60L3	62	G08G1	0.0213	G06N5	22	G16B40	0.0135	G05B15	39	G01R31	0.0401
G06F16	0.0295	B66F9	57	G06V20	0.0197	B33Y50	22	G06N7	0.0133	G06F18	38	G06F17	0.0388
G01N33	0.0237	H02J7	55	G06F17	0.0191	B29C64	22	B29C64	0.0123	G05B23	36	H01M10	0.0388
G06F40	0.0172	G10L15	55	G06F16	0.0188	G06N7	22	G05D1	0.0122	G06N5	35	G06F11	0.036
G06F17	0.017	B60L11	52	G06K9	0.0186	G06F40	20	G06Q30	0.0122	G06K9	34	C25C3	0.0352
G06F11	0.0167	G06F17	51	B23K31	0.0176	G06F3	20	G06V10	0.0116	G01N33	33	G16C20	0.0303
G06N7	0.012	G06K9	49	B25J13	0.0159	H04L9	18	G06K9	0.0116	H02J13	32	B01J19	0.0284
G06T5	0.0109	G06F9	47	H04W4	0.0158	B33Y10	18	G16B5	0.0097	G05F1	32	F27D17	0.0256

s	181	*Number of nodes*	357	*Number of nodes*	163	*Number of nodes*	292
s	1027	*Number of edges*	2790	*Number of edges*	727	*Number of edges*	1656
	0.063	*Graph density*	0.044	*Graph density*	0.055	*Graph density*	0.039

xpresses whether a node occupies a structurally central position in the network; graph density measures how connected the graph is [32], [105], [107], [131], [132].

G06K9	55	H04W4	74	G06V10	46	G06F30	23	G06N20	39	G05B13	44	G06F18	38
G06N20	55	B62B5	66	G06T7	40	G06F11	20	G06F17	35	G06N3	40	G06F17	36
G06Q50	51	G06Q10	64	G06V20	40	G06N7	18	G06F16	29	G05B15	36	G06F16	34
G06Q10	49	H04L29	64	G06K9	38	G06N20	17	G05B13	26	G06N20	35	G06F30	33
G01N21	47	B25J9	60	G06Q50	37	G06F17	16	G06K9	26	G06F17	35	G05B19	30
G06F30	41	B60L3	54	G06F16	36	G06Q30	14	G06Q30	25	G05B23	32	G01N33	29
G06F11	35	H02J7	53	G06F17	34	B33Y50	13	G06N5	20	G05F1	32	G06V10	28
G06F16	31	B60L11	52	H04L67	31	G06F16	13	G06F40	19	G06F11	28	G06K9	28
G06F40	27	G06Q50	49	G06N20	30	G06F3	12	H04L9	18	G06N7	28	G06N5	25
G06N7	26	B60Q5	47	G06Q10	28	G05B13	11	B33Y50	18	H02J13	28	G06F11	25
G06V20	26	B60L15	44	G06F30	27	B29C64	11	G06F11	18	G06Q30	28	B23K26	22
G06F17	26	B66F9	43	B25J11	27	B23P17	10	G05B19	17	G01R22	25	G05D1	21
G06T5	25	G06T7	39	G10L15	27	B23K26	10	G06V10	17	G06F30	23	G16C20	20
G05B19	23	G06Q30	39	B25J19	24	B23K31	10	G06F18	17	G01R1	23	B33Y10	19
G06N5	23	B60K7	39	B25J13	24	B23P23	10	B33Y10	16	F24F11	22	B33Y50	19
B33Y50	21	G07C5	39	B64C39	23	B23K20	10	A61B5	14	G01R31	18	C25C3	19

etection		**Advanced robotics**				**Scheduling**				**Resource optimization**			
Betweenness 2021–2023		*Betweenness 2011–2021*		*Betweenness 2021–2023*		*Betweenness 2011–2021*		*Betweenness 2021–2023*		*Betweenness 2011–2021*		*Betweenness 2021–2023*	
G06N3	0.2585	G05D1	0.3696	G05D1	0.3929	G05B19	0.2436	G06N3	0.4373	G06Q50	0.2267	G06N3	0.4758
G06T7	0.1656	G05B19	0.1290	B25J9	0.1615	G06Q10	0.1990	G06Q50	0.1401	H01M8	0.1599	G06N20	0.0989
G06V10	0.1133	B25J9	0.0786	G06N3	0.1526	G06N3	0.1555	G06Q10	0.0926	H02J3	0.1191	G01N33	0.0881
G06F18	0.1053	F01D5	0.0687	G05B19	0.0875	G06Q50	0.0967	G06F30	0.0675	G05B19	0.1012	B23K26	0.0680
G06K9	0.0803	G06Q10	0.0450	G06V10	0.0544	G05B13	0.0601	G06N20	0.0672	G06Q10	0.0941	G06F18	0.0665
G06N20	0.0569	G01C21	0.0414	G10L15	0.0466	G06F30	0.0325	G05B13	0.0469	G05B13	0.0892	G06Q50	0.0659
G01N21	0.0549	G06Q50	0.0379	G06T7	0.0413	G06F11	0.0235	G06F17	0.0449	C01B3	0.0782	C25C3	0.0645
G06Q50	0.0532	G08G1	0.0272	G06F16	0.0385	G06F19	0.0207	G05B19	0.0428	G01R31	0.0746	G06Q10	0.0534
G06Q10	0.0432	G06N20	0.0266	G06V20	0.0383	G06N7	0.0169	G06F16	0.0249	G06N99	0.0688	B01J19	0.0498
G06F30	0.0326	H02J7	0.0264	G06N20	0.0369	G06N20	0.0123	G16C20	0.0225	B33Y50	0.0566	F27D17	0.0478
G01N33	0.0274	H04W4	0.0248	G06K9	0.0333	G06Q30	0.0093	G16B40	0.0203	G06N20	0.0496	G06F30	0.0477
G05B19	0.0246	G06T7	0.0172	G06F17	0.0305	G06F17	0.0093	G06K9	0.0192	G06F11	0.0485	G06F17	0.0462
G06F11	0.0219	B62B5	0.0130	G06F30	0.0288	G06F16	0.0077	G06V10	0.0178	G06N3	0.0479	G06F16	0.0451
G06F40	0.0203	B25J19	0.0103	G06Q50	0.0261	B29C64	0.0069	G16B5	0.0137	G06F30	0.0402	G16C20	0.0411
G06F16	0.0176	B60L11	0.0101	H04L67	0.0232	G06F3	0.0052	B33Y50	0.0116	G06F17	0.0402	G06K9	0.0405
G06F17	0.0173	H04L29	0.0099	B25J11	0.0188	B33Y50	0.0051	G06N5	0.0105	H01M10	0.0394	G06V10	0.0314
G06T5	0.0133	B64C39	0.0094	G05B13	0.0183	G05D1	0.0041	G06N7	0.0085	H02J7	0.0361	C25C7	0.0268
G06V20	0.0128	B25J13	0.0090	B62D63	0.0176	G06F9	0.0010	G16C60	0.0085	G06T7	0.0316	G16C60	0.0210
B23K37	0.0126	B60L3	0.0073	B23K31	0.0169	H04L29	0.0009	G06Q30	0.0082	G05B15	0.0295	G05B19	0.0204
G16C60	0.0117	B60L50	0.0073	B64C39	0.0146	G06F21	0.0008	G06F18	0.0066	G05D3	0.0231	G06F40	0.0181

expresses whether a node occupies a structurally central position in a network; graph density measures how connected the graph is [32], [105], [107], [131], [132].

detection		**Advanced robotics**			**Scheduling**			**Resource optimization**		
1– 21	*2022– 2023*		*2011– 2021*	*2022– 2023*		*2011– 2021*	*2022– 2023*		*2011– 2021*	*2022– 2023*
5	159	*Number of nodes*	214	231	*Number of nodes*	86	114	*Number of nodes*	167	193

2023	2023	1.243	31.40%	28.90%	**27.40%**	0.972	0.899	**0.975**	0.014	0.021	0.013
2024	2024	1.990	35.40%	**24.70%**	29.80%	0.921	0.869	**0.935**	< 0.001	0.007	< 0.001
2024	2024	1.862	20.40%	20.10%	**15.10%**	0.982	0.936	**0.987**	< 0.001	0.002	< 0.001
2025	2023	1.242	26.00%	28.00%	**23.00%**	0.958	0.896	**0.974**	< 0.001	< 0.001	< 0.001

ogy to pass through the growth stage and reach maturity, and the midpoint is the exact point at which the growth trend enters the maturity stage. Accordingly, before the midpoint year,

-value of the F-test assesses whether the overall model is a good fit for the data [14], [32], [41], [133].

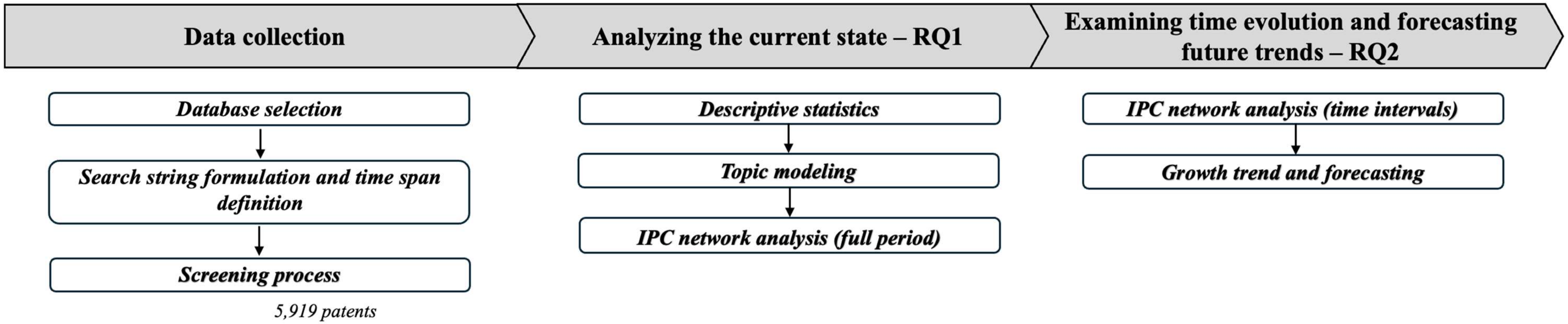

Fig. 1: Methodological approach to patent analysis adopted in this paper.

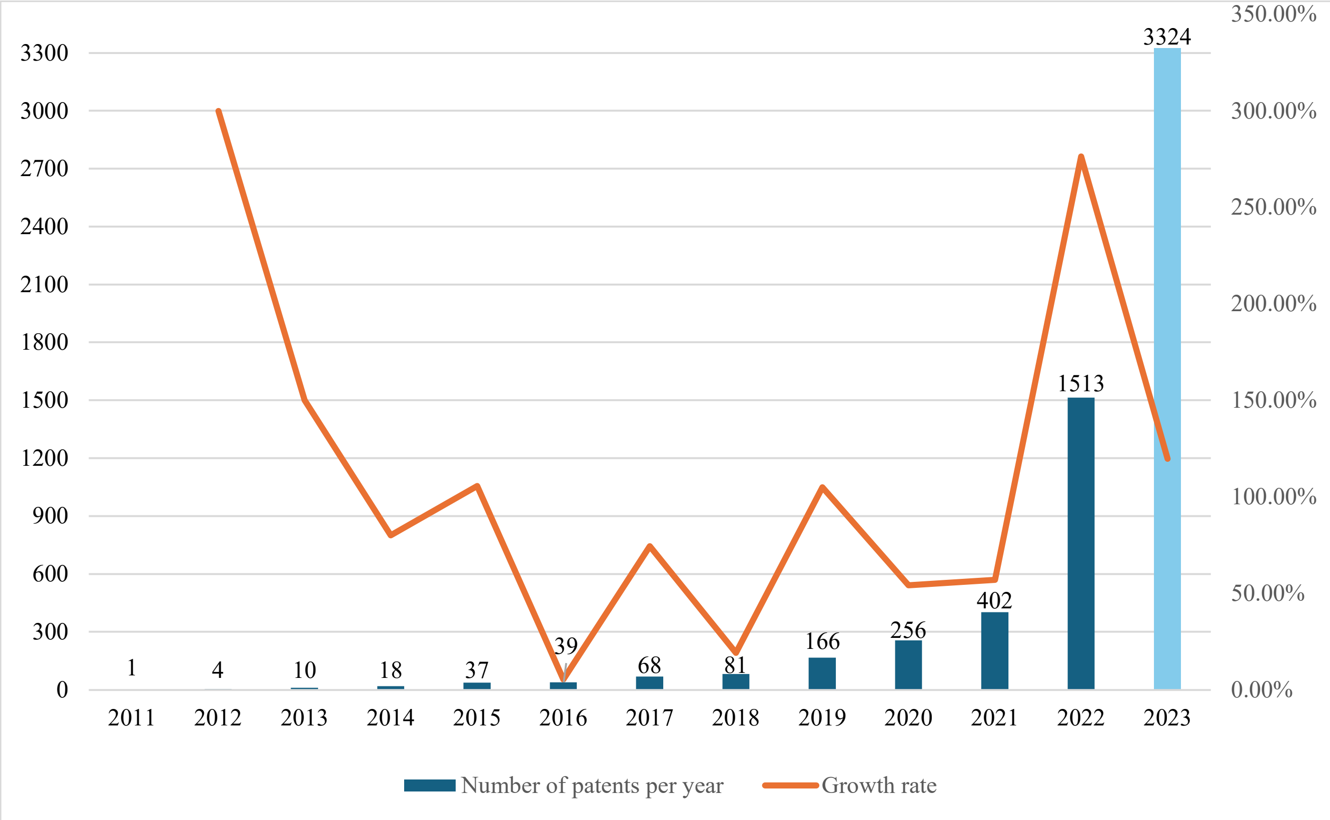

Fig. 2: Temporal trends of patents related to AI solutions to address climate change in manufacturing.

Note: 2023 is shaded as considered patents are up to November 2023.

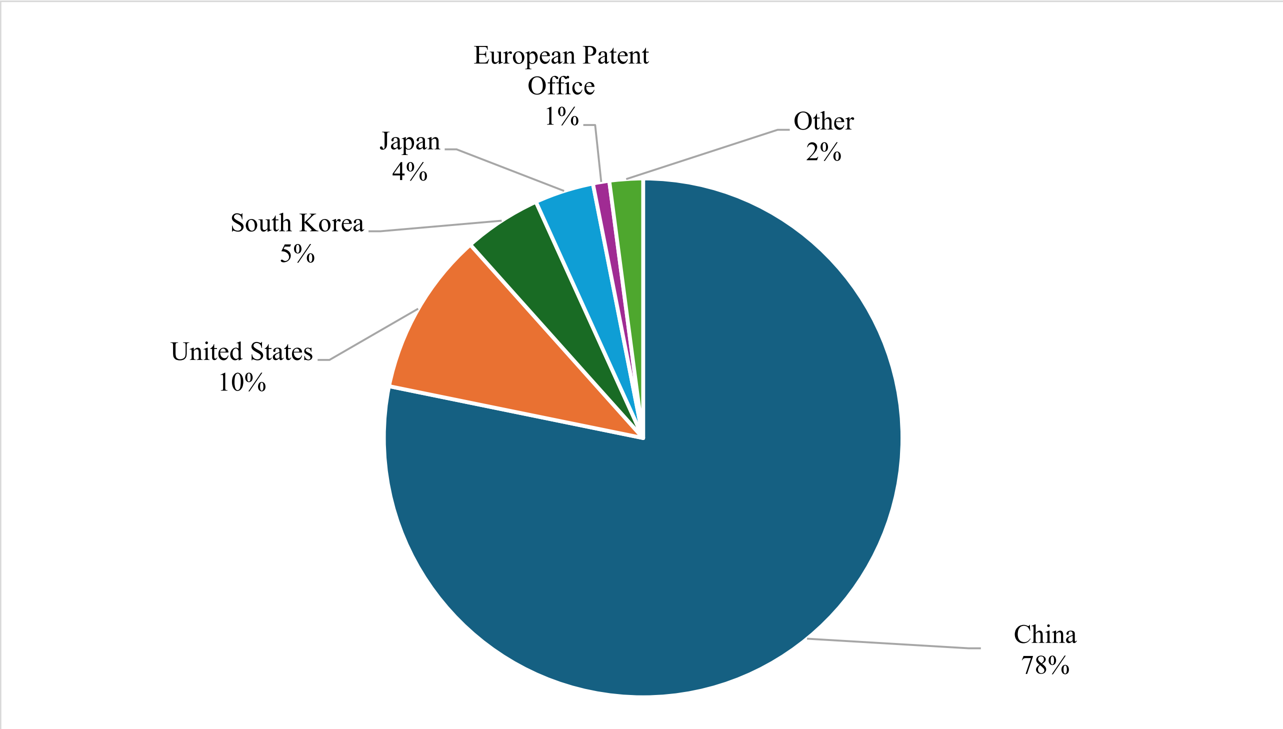

Fig. 3: % of patent applications by priority country.

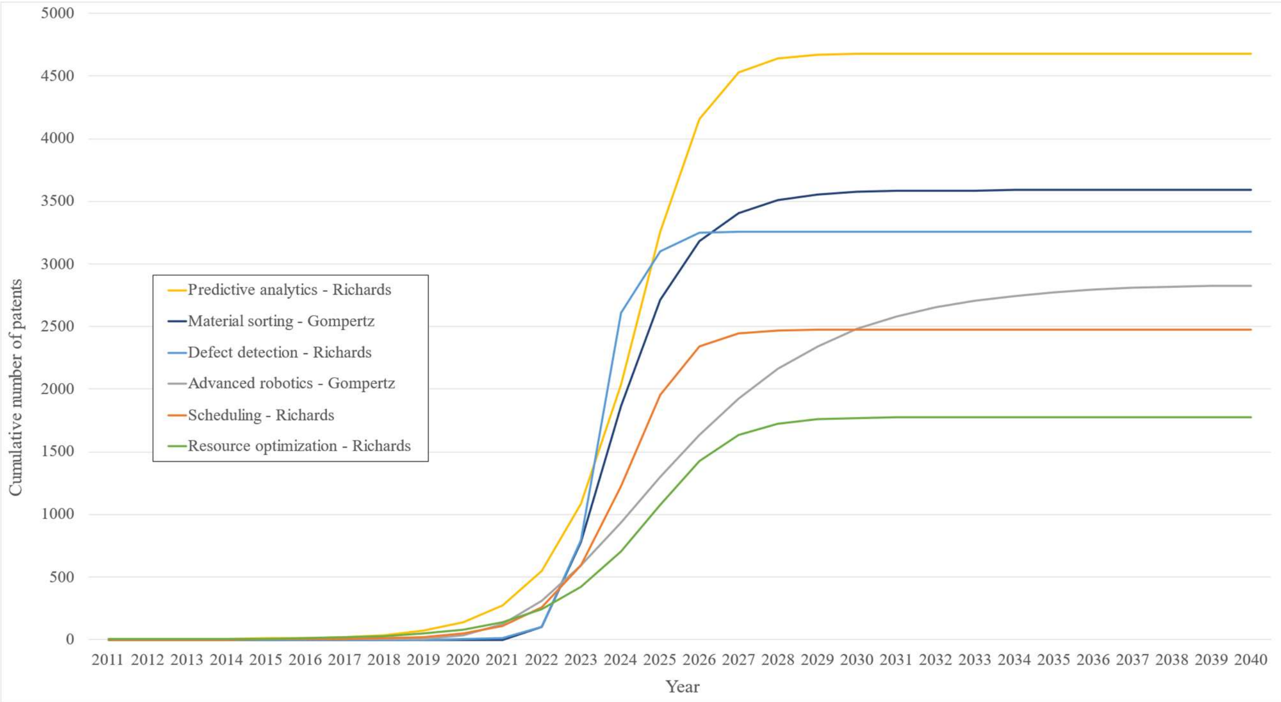

Fig. 4: Growth curve forecast.

Note: the specific parameters of the adopted models are reported in Table 7.

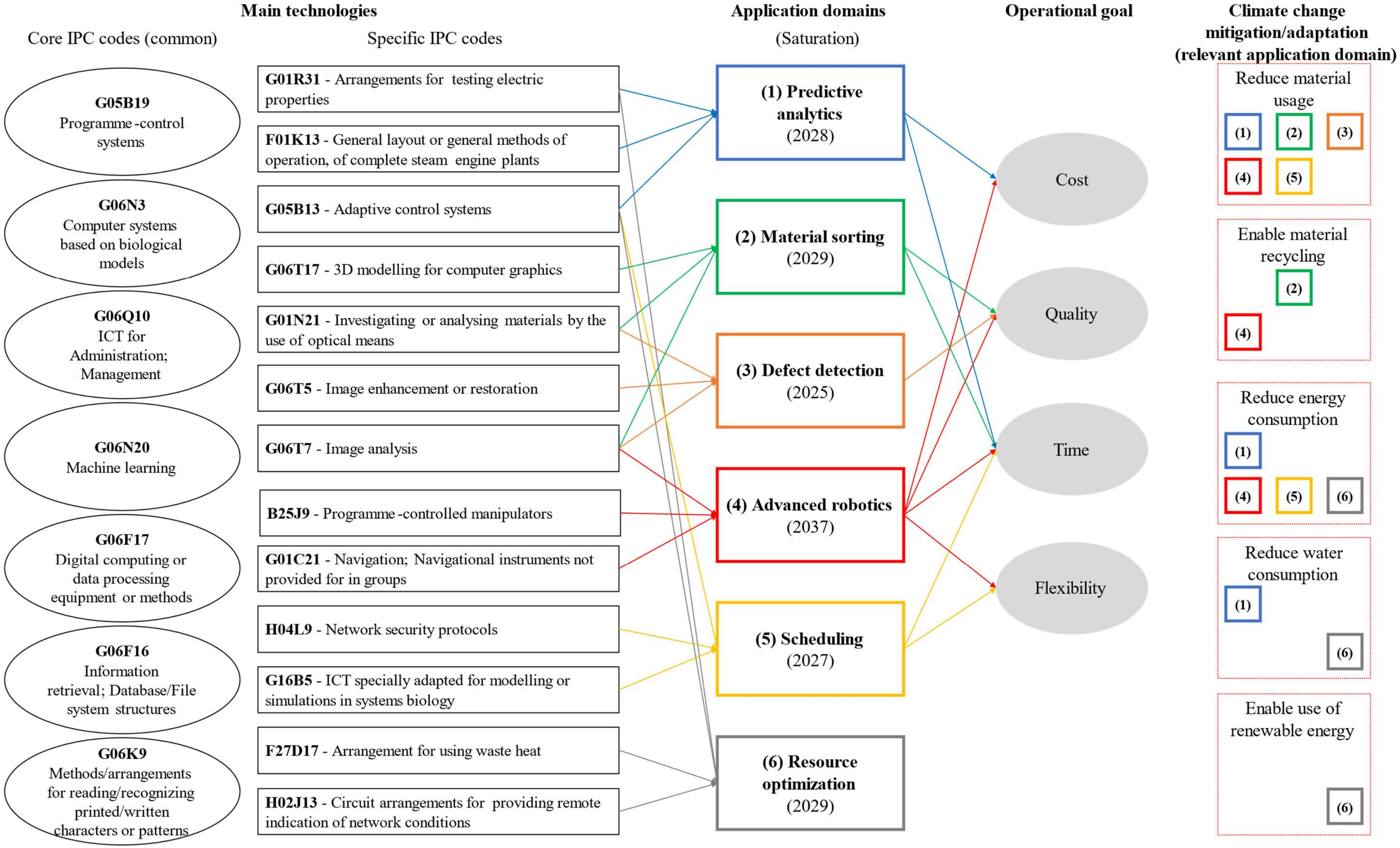

Fig. 5: Summary framework.