Tracking AI in climate innovation

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Innovation in artificial intelligence (AI) is spreading rapidly in many areas of technology, and AI technologies may be of help to mitigate and adapt to climate change. However, previous studies of AI in the climate context mainly rely on expert judgement of the research literature, not large-scale data. Here, we present a new approach to analyzing the relation between AI and climate innovation on the economy-wide scale. We analyze over six million patents from the past 45 years from the United States, and find that the greatest amount of climate AI innovation has occurred in transportation, energy, and manufacturing technologies. Green ICT and climate adaptation technologies is where AI innovations have higher shares, and breakthrough innovations have made up a larger share in adaptation technologies compared to technologies for climate mitigation. We estimate the difference that AI makes with statistical analysis: AI in mitigation and adaptation technologies is associated with 30-100% more subsequent innovations. Our approach provides new capabilities to track the exponential growth of AI in climate innovation.

A range of artificial intelligence technologies are rapidly being developed with high expectations of technological innovation and economic growth. AI might also contribute to increasingly effective climate change mitigation and adaptation technologies. However, an increasing capability to automate and transform production, equip industries with new tools, and draw increasing government support, also means that technological breakthroughs could lead to a higher demand for computing power, larger carbon footprints, shifts in patterns of electricity demand, and an accelerated depletion of natural resources. Whether the net effect of AI on the climate system will be ameliorative or detrimental is currently an open question: Concerns about the effects of AI have recently been followed by calls for new regulations and increased international oversight. This suggests a need for increased research and analysis capabilities to track, clarify, examine, and understand these new technologies. Here, we present a new approach based on large-scale data to track AI innovation in technologies that can contribute to climate adaptation and mitigation.

The initial research into the connection between AI and climate change has often rested on the framework of UN Sustainable Development Goals. Here, experts find both positive and negative effects of AI. The UN goals provide a broad social and political context, but covering them all might currently be too broad a task for a single project or data source. In this study, we restrict ourselves to climate change and use data sources for this specific issue to investigate the effect of AI innovation. For climate change, expert analysis has previously suggested that machine learning could have broad potential in both mitigation and adaptation strategies, with a mixed message regarding the potential net effect on the climate system.

Expert-based reviews can integrate deep knowledge from different domains, even when the data are scarce. However, experts often find it challenging to unpack and
Technologies | All Patents | AI Patents | AI Share | CPC code
--- | --- | --- | --- | ---
Adaptation to climate change | 45,993 | 789 | 1.72% | Y02A
Buildings/housing | 48,561 | 605 | 1.25% | Y02A
Carbon capture and storage | 5,743 | 5 | 0.09% | Y02B
Green ICT | 41,681 | 924 | 2.22% | Y02B
Energy generation/distribution | 174,907 | 1,123 | 0.64% | Y02E
Production and processing | 105,434 | 1,180 | 1.12% | Y02P
Transportation | 111,196 | 1,416 | 1.27% | Y02T
Waste water and management | 24,450 | 61 | 0.25% | Y02W

Table 1: Summary metrics for United States patents in technologies that can mitigate or adapt to climate change, 1976-2019. In some cases, we have shortened the names.

fully explain their partially automatic judgment process. Moreover, expertise does often not translate easily from one domain to another. There is evidence that expert forecasts can be improved on by models that have access to additional quantitative historical data. To scale up and cover a technological literature spanning many areas is a challenge for any team of researchers, and there could be a potential to complement expert analysis in tracking AI innovation with large volumes of available data about technological innovation in various economies. Here, we combine data from national patent offices and intellectual property organizations regularly used to monitor innovation in large economies.

Patents are possibly the most detailed record of technological innovation. National patent offices have analyzed and classified millions of innovations using international classification systems. Patent offices search for prior art to judge whether claimed innovations are sufficiently novel before granting patents: Classification codes provide the primary tool to make technologies searchable. Our approach is to combine separate data sources developed for classifying low carbon and AI innovations to find patents that are both. First, we use a classification system initiated by the European Patent Office for monitoring selected technologies related to mitigating, or adapting to, climate change. Second, we find the innovations that can be considered to be AI, according to a recent method developed by the World Intellectual Property Organization (WIPO) that can be automated computationally. The WIPO method labels patents as AI based on patent classifications, a mix of keywords from the patent texts, and a set of logical operations on classifications and keywords. Third, we combine these two different types of data sources we enable the first large-scale study of the link between AI and climate innovations.

More specifically, our data are as follows. First, we collect historical data about six million granted patents publicly available from the US Patent and Trade-

\(^1\)The resulting data and the current version of our tool for exploring, searching, and analyzing the connection between AI and climate innovations is available at http://greentech.ai
mark Office (USPTO) for the period from 1976 to 2019, up to when the WIPO method for finding AI patents was developed and validated. We restrict the data to the US as it is a leading economy, and US patents have been found to well represent the frontier of technological innovation. Second, we extract technology classification data for the innovations, including current labels for climate innovations: The Cooperative Patent Classification (CPC Y02) subclass “covers selected technologies, which control, reduce or prevent anthropogenic emissions of greenhouse gases [GHG], in the framework of the Kyoto Protocol and the Paris Agreement, and also technologies which allow adapting to the adverse effects of climate change.”

Third, we apply the method developed by WIPO to label matching patents in the same data as AI for further analysis. For further details about classifications, see Methods. For summary metrics describing AI patents in climate innovation, see Table 1.

In Fig. 1a we see how both climate innovations together with AI have demonstrated strong growth in the past decade. Fig. 1b illustrates how AI, climate innovations, and especially the climate AI patents all have undergone exponential growth. Fig. 1c shows that more than half of all AI innovations in climate patents since 1976 are found in technologies for transportation, energy, and production. AI in adaptation and buildings/housing technologies have lagged somewhat behind in absolute numbers. For waste management and carbon capture/storage, we see there are clearly very few data. Fig. 1d shows how green ICT and adaptation technologies are areas where AI has had large overall impact in the last few years. Taken together, the number of unique patents that are both AI and climate innovations between 1976 and 2019 is 4390; around 1.5% of the total climate innovations and 2.7% of the AI technologies.

To examine if AI makes a difference in climate innovations, we choose to analyze the forward citations subsequent patents make to a given patent after its publication. For a given patent, this reflects the number of subsequent innovations that patent offices deep to build upon it. These forward citations are often considered to be one of the most important indicators of technological impact of a patented invention and can be seen as spillovers to the larger economy. Harhoff et al. found that the economic value of individual patents, measured through a survey with the assignees, is positively correlated with the number of forward citations. Hall and Trajtenberg also showed that the average number of forward citations per patent correlated strongly with the market value of firms and they concluded that if a firm’s quality of patents increases so that, on average, the patents receive one additional citation, the firm’s market value increases by 3%. Moreover, forward citations are positively correlated with patent assignees’ willingness to pay renewal fees, which indicates the economic value of cited patents. One can also search for technological breakthroughs depending on the accumulated forward citations in the years after which a patent was granted: Squicciarini et al. define breakthrough inventions as the top 1% cited documents for each year, and consider a three-year forward
Figure 1: AI patents in climate innovations. Fig. 1a shows a steeper rise starting around 2010. Fig. 1b shows exponential growth in climate AI (linear on log scale). Figs. 1c and 1d illustrate how transportation, energy, and production mitigation technologies have accumulated the most AI patents, while the smaller classes of green ICT and adaptation technologies have larger shares of AI innovations.
citation count. Benson and Magee\textsuperscript{26} constructed a metric they term \textit{immediate importance} as the average number of citations that a patent receives within three years of publication. Consistent with the previous literature, we examine the effect on a three-year horizon and examine the difference that AI is related to in terms of subsequent innovations. We also consider breakthrough inventions as the top 1\% cited patents in a technological area in a given year.

Fig. 2 shows the groups of climate innovation patents from Table 1, with each group split into AI and non-AI. Two aspects can immediately be seen for each group. First, the average forward citation count is greater for both AI and climate innovations, representing more subsequent innovations on average. Second, zooming in on the highly cited breakthroughs (the highest counts in Fig. 2), we see that most highly cited patents appear to be non-AI innovations. In total counts, AI is related to more innovations on average but has fewer of the highly cited breakthroughs. However, as we shall see, this does not address the fact that AI has a much smaller share of total innovations. In the following, we estimate the predictive difference in average forward citations by including controls and test for a difference after adjusting for the group size. We skip patents related to CCS and waste technologies, as the volumes of AI patents are so small that statistical conclusions would be too preliminary at this point.

To estimate the predictive difference of AI on patent forward citations, we use count regression modeling of the forward citations on a three-year horizon, limited to patents granted in the previous decade (2010-2017, permitting a 3-year horizon). We control for the effects of difference in year, technological area that the patents are from, and other factors in line with previous work on modeling forward citations for patents\textsuperscript{28} (for details, see Methods and S.I.). In Fig. 3, we see the results from the regression modeling for the climate innovation areas, and ten technology areas (also defined by CPC classifications) where AI patenting has been most prevalent. We find the difference that AI makes for the average number of forward citations: For most technologies, AI is associated with more subsequent innovations, even after controlling for other factors. Among climate innovations, AI was associated with a $30-100\%$ increase in forward citations (the predictive differences are statistically significant). Among the technologies with climate innovations, technology for buildings and green ICT showed the greatest effect of AI, with adaptation and energy technologies on average showing a weaker effect. Compared to other technologies with many AI patents, the effect of AI in mitigation and adaptation technologies either corresponds to or exceeds the typical effects of AI on forward citations, except for what we can see in communication technologies.

Our results so far describe the difference AI makes to the average, representing more citations in total. However, note that an increase in averages does not necessarily correspond to an increase in the highly cited technical breakthroughs. We also saw in Fig. 2 that there are fewer AI breakthroughs in total, as expected because of the smaller volume of AI patents, and Fig. 1 showed that AI technologies have
Figure 2: Comparing AI and non-AI patents in climate innovations, 2010-2017: AI patents are on the average associated with more subsequent innovation. The total number of AI breakthroughs is still fewer, in line with fewer AI patents. Dashed vertical lines show boundaries for breakthroughs (for forward citation counts above the 99th percentile). Boxplot whiskers are located at 5th and 95th percentiles. For plotting, a log plus one transformation was used.
Figure 3: Comparing AI in climate innovation areas to AI in other areas using count regression models. The estimated predictive difference of AI is statistically significant in the range of 30-100% more subsequent innovations in the groups of climate innovations. This effect is as strong or stronger compared to most other technologies in which AI patents are common, except for certain communication technologies. The CCS and waste technologies were left out due to small sample sizes. A stated p value of 0 should be interpreted as being very close to 0 ($< 2e-16$).
undergone a recent surge. One question is if there are similar patterns and shares of breakthroughs in AI innovations as in other areas.

To examine if AI innovation is associated with differences in the share of technological breakthroughs, we consider in each group the 1% patents per year with the most forward citations in the three years following publication. For a technological area, we take the cumulative experience of AI innovation as the total count of AI patents in the area. Then, we compare how counts and shares of AI breakthroughs has grown in climate innovation and other technologies.

Fig. 4 shows that the large groups of climate mitigation technologies have been associated with similar AI breakthrough rates as other technologies. We see that for adaptation technologies, AI breakthrough counts is higher relative to number of AI patents compared with other technologies. A quantile hypothesis test (see Methods) also suggests that breakthroughs have made up a higher share of climate adaptation technologies has had a larger share of AI breakthroughs, as shown in Fig. 5. Estimates for the other groups are more uncertain: The wide intervals suggest that the current evidence is too weak to strongly rule one way or the other about AI breakthroughs in the areas of climate mitigation, in contrast to climate adaptation technologies. For climate mitigation technologies, this uncertainty means that the jury is still out with respect to the role of AI in breakthroughs.

Taken together, we have shown that we can find historical and recent patterns of AI in climate innovation by combining new methods and data sources that describe innovation on the level of an economy. We estimate artificial intelligence innovations in adaptation and mitigation technologies with 30-100% more subsequent innovations. Breakthroughs have made up a larger share in adaptation technologies than in mitigation. A good question is whether these patterns will continue and what can be accurately forecasted with further analysis. With our capabilities to track climate and AI innovation, future work can complement expert studies in the area with large-scale quantitative analysis. We see the potential to increase our use of large-scale data sources to study whether AI innovations lead to the ends we seek.
Figure 4: Cumulative experience of AI innovation in technological areas and AI breakthrough counts in the same area. The trajectories represent adaptation and mitigation technologies, as well as the 50 largest technologies (largest by patent volume). In climate adaptation technologies, the breakthroughs have made up a larger share of the AI patents compared to groups of mitigation technologies. Transport technologies have most observed breakthroughs, in line with having the most AI patents.
Figure 5: Estimated differences between the 99th percentile for AI and non-AI patents in adaptation and mitigation technologies. For adaptation, AI technologies is clearly associated with more breakthroughs. For green ICT, production, and transport, the direction of estimates suggest similar results. However, wide confidence bands reflect a large statistical uncertainty because a small absolute number of AI innovations. For mitigation technologies, the jury is still out with respect to AI breakthroughs: More data are needed.
Methods

Our raw data are the texts of six million US patents from 1976 to 2019, from which we extract and generate the most covariates. We label patents as climate innovations (mitigation or adaptation technologies) if they are classified with a CPC code of Y02, and apply the WIPO method to the patent classifications and raw texts to classify patents as AI. We use current and multiple CPC classifications per patent (where possible) to compare the predictive effect of AI on forward citations in groups of technologies extracted according to corresponding CPC codes. Classifications are further sub-divided with one or more labels according to what part of climate change they relate to (6 different sections). We also include classifications of technologies according to their wider functions.

For a statistical analysis with regression modeling, we make the following restrictions by pre-processing the data. First, we filter out the top 1% of the most highly cited patents to successfully get regression model residuals that indicate a good model fit to the population (outliers are difficult to predict and can skew the regression model fit). Second, we remove subgroups so small they lack patents in at least one of the years between 2010 and 2017 (this is around 1% of subgroups, representing technology areas with very little patenting activity). Third, for regression, we used data between 2010-2019 to zoom in on the most recent period which is a continued rise of AI, but where a majority emerged in the past decade. Finally, it should also be noted that we fit the same (equally specified) regression model to the separate groups of technologies when we make comparisons of the effect of AI between technologies using regression fits. This allows the influence of the different parameters to vary across different technologies, as expected.

Our statistical investigation shows that the target count variable of forward citations is zero-inflated, heavy-tailed, and related to grouping by different technologies. The Poisson model served as a natural starting point for count data, but a direct comparison of mean and variance showed that the target variable is over-dispersed. To adjust for this, we also fit negative binomial models. Here, an additional size parameter controls the degree of over dispersion compared to a Poisson distribution, and a test showed it to be statistically significant. Despite this, an analysis of the residuals for model fits indicated a lack of fit as well as a grouping in the data. Therefore, we use a Generalized inverse Gaussian distribution (Sichel distribution), as this can model highly dispersed count data in other domains. To fit the model and adjust for grouping, we use the GAMLSS methodology. Here, an analysis with the randomized quantile residuals indicates a good fit of the model to the data (for details, including Q-Q plots for approximate normality, for more see S.I.).

The covariates/controls include indicator variables for patents being AI, low-carbon, an organization as an inventor, and whether patents have been classified as CPC groups/sub-groups. Furthermore, we adjust for grant year, number of patent claims, number of inventors, and three variables for citation counts to other publica-
tions: by other patents, by research literature, and by other literature. Finally, we include technology cycle time (TCT) but as a discretized covariate, as an exploration of the data (in the S.I.) suggests that TCT is non-linear and varies between different groups of technologies.

The regression model for the conditional mean of forward citations $y$ is specified in short-hand notation which leaves out the term coefficients in $\beta$:

$$x_i \beta = \log E[y_i],$$

where

$$x_i = \text{tct\_type}_i + \text{grantyear}_i + \text{tct\_type}_i \times \text{grantyear}_i + a_i \times \text{green}_i + \text{organizational}_i + \text{claims\_log}_i + \text{individual\_inventors\_log}_i + \text{patent\_citations\_log}_i + \text{research\_citations\_log}_i + \text{other\_citations\_log}_i + (\text{indicator\_variables\_for\_groups/subgroups})_i$$

For more details and model diagnostics, see the results in S.I.

To compare shares of breakthroughs, we formally test if there is a difference for the largest technology areas. We do a quantile comparison across two groups and adjust for their sizes by resampling them using percentile bootstrap to compute confidence intervals for the difference between the two groups. If one distribution has a higher quantile than the other, it indicates that innovations from this distribution more often leads to breakthroughs. Specifically, the null hypothesis is taken to be $H_0: \phi_{q1} = \phi_{q2}$ for a specific quantile, where $\phi_{q1}$ and $\phi_{q2}$ are taken to represent the 99th percentile. By resampling the two distributions and examine the results under the null hypothesis, we estimate the difference $\phi_{q1} - \phi_{q2}$ for the thresholds with the 1% most cited patents.

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