# Quantifying the Benefit of Artificial Intelligence for Scientific Research

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The ongoing artificial intelligence (AI) revolution has the potential to change almost every line of work. As AI capabilities continue to improve in accuracy, robustness, and reach, AI may outperform and even replace human experts across many valuable tasks. Despite enormous efforts devoted to understanding AI's impact on labor and the economy and its recent success in accelerating scientific discovery and progress, we lack a systematic understanding of how advances in AI may benefit scientific research across disciplines and fields. Here we develop a measurement framework to estimate both the direct use of AI and the potential benefit of AI in scientific research by applying natural language processing techniques to 87.6 million publications and 7.1 million patents. We find that the use of AI in research appears widespread throughout the sciences, growing especially rapidly since 2015, and papers that use AI exhibit an impact premium, more likely to be highly cited both within and outside their disciplines. While almost every discipline contains some subfields that benefit substantially from AI, analyzing 4.6 million course syllabi across various educational disciplines, we find a systematic misalignment between the education of AI and its impact on research, suggesting the supply of AI talents in scientific disciplines is not commensurate with AI research demands. Lastly, examining who benefits from AI within the scientific workforce, we find that disciplines with a higher proportion of women or black scientists tend to be associated with less benefit, suggesting that AI's growing impact on research may further exacerbate existing inequalities in science. As the connection between AI and scientific research deepens, our findings may have an increasing value, with important implications for the equity and sustainability of the research enterprise.

## Main text

The rapid advances in artificial intelligence (AI) may lead to massive value creation and capture across many facets of human society<sup>1-4</sup>, creating enormous social and economic opportunities<sup>5-7</sup>, and just as many challenges<sup>8-14</sup>. Despite extensive efforts devoted to understanding the impact of AI on the labor market and the economy<sup>15-18</sup>, it remains unclear about the impact of AI on the growing research enterprise. Indeed, recent AI advances have shown promises to achieve and, in some cases, exceed expert-level performance across many economically valuable tasks<sup>19-24</sup>. As society is preparing for the moment when AI may outperform or even replace human recruiters, bankers, doctors, lawyers, composers, and drivers, an important question arises: What is the impact of AI in advancing research across scientific disciplines and fields?

A better understanding of AI's impact on science may not only help guide AI development, bridging AI advances more closely with scientific research, but also hold implications for science and innovation policy. This is especially the case given AI's recent remarkable success in advancing research frontiers across several fields<sup>25-32</sup>, from predicting the structure of proteins in biology<sup>33-35</sup> to designing new drug candidates in medicine<sup>36-38</sup>, from discovering natural laws in physics<sup>39,40</sup> to solving complicated equations and discovering new conjectures in mathematics<sup>41-43</sup>, from controlling nuclear fusion<sup>44</sup> to predicting new material properties<sup>45-47</sup>, from designing taxation policy<sup>48</sup> to suggesting democratic social mechanism<sup>49</sup>, and more<sup>50-52</sup>. These advances raise the possibility that, as AI continues to improve in accuracy, robustness, and reach, it may bring meaningful benefits to science, propelling scientific progress across a range of research areas while significantly augmenting researchers' innovative capacities.

Yet, at the same time, despite AI's rapid progress and its broad applications to several domains, there is substantial skepticism about whether today's AI is capable or significant enough for advancing scientific research. Indeed, most current AI applications belong to the category of "narrow AI,"<sup>53-55</sup> which tackles specifically defined problems, and hence may not be suitable to fulfill the broad range of tasks that scientific research demands<sup>3,15</sup>. Further, to the extent that AI may provide automated solutions to an existing problem, science is not only about solving well-defined problems but spotting new frontiers and generating novel hypotheses<sup>56</sup>. These views paint a more nuanced picture of AI's applicability to advancing science, suggesting AI may be better suited to perform some research-related tasks than others<sup>3,9,57</sup>.

Building on the growing literature on the future of work<sup>3,57-62</sup> and the science of science<sup>63-67</sup>, here we develop a quantitative framework for estimating AI's impacts on scientific research (see Methods for details). Our primary dataset contains 87.6 million publications from the Microsoft Academic Graph (MAG) (1960-2019)<sup>68</sup>, spanning 19 disciplines and 292 fields (see Supplementary Note 1.1 for details). We then integrate this dataset with 7.1 million patents granted by the U.S. Patent and Trademark Office (USPTO) (1960-2019; see Supplementary Note 1.2). We follow prior studies to identify AI-related papers and patents using a keyword-based approach (see Supplementary Notes 2.1 and 3.1 for details)<sup>67-69</sup>, allowing us to measure AI's impact on scientific research at two levels. First, we estimate the direct use of AI using an "AI n-gram framework" (Figure 1a). Specifically, we first extract n-grams (bigrams and trigrams) from the titles of AIrelated papers and calculate their frequency of occurrences to approximate cumulative AI advances<sup>67</sup>. We then repeat this n-gram measurement for papers published in every field and year, allowing us to calculate the weighted frequency of AI n-grams to approximate the direct use of AI in each field and year. Second, motivated by the future of work literature<sup>57-59</sup>, we estimate the potential impact of AI using an "AI capability-field task framework" (Figure 2a). Specifically, we infer the capabilities of AI (i.e., what AI can do) by extracting verb-noun pairs from the titles of AI-related papers and patents using natural language processing (NLP) techniques and calculate their relative frequency<sup>70-72</sup>. We then estimate the basic tasks of each field (i.e., what a field does) by calculating the relative frequency of verb-noun pairs extracted from the titles of papers published in each field and year. Matching prevalent tasks in a field with inferred AI capabilities allows us to approximate AI's potential impact on the field (see Methods for details).

## Results

#### The widespread use of AI across the sciences

Overall, we find that AI research presents a dynamically evolving landscape (Figure 1bc). While the dominant AI n-grams in 2019 were "machine learning," "convolutional neural network," "deep learning," "artificial intelligence," and "deep neural network" (Figure 1b), some AI n-grams emerged only recently (e.g., "generative adversarial network"), some remained dormant for a long period but rose to prominence in recent years (e.g., "deep learning"), and some reduced in popularity over time (e.g., "support vector machine") (Figure 1c). Amidst this rapidly evolving landscape of AI research, there has been a precipitous rise in the use of AI by other disciplines (Figure 1d). For example, in 2019, "neural network" is the 10<sup>th</sup> mentioned n-gram by physics papers, higher than canonical focuses in physics such as "gravitational wave," "magnetic property," or "monte carlo" (Supplementary Figure S2). The increasing use of AI by other disciplines raises an interesting question: how does the impact of such AI-using papers compare with other papers in the same discipline? To answer this question, we calculate the hit paper probability as being in the top 5% by citations in the same field and year. We find that, for a majority of disciplines, papers that mention AI-related terms in their titles not only are more likely to be hit papers within their disciplines (Figure 1e) but also receive more citations from other disciplines compared to non-AI-using papers (Figure 1f). This impact premium appears stronger for disciplines with a

lower overall propensity of using AI (Supplementary Figure S4), suggesting that disciplines that seem distant from AI may experience substantial benefits from using AI to advance their research.

The dynamic landscape of AI advances prompts us to further explore how the direct use of AI in scientific research has changed over time. Specifically, we calculate the direct AI impact score for each discipline in 2000-2019 (see Supplementary Figure S3 for the results covering a longer period of 1960-2019). We find that, while disciplines overall used more AI in their research over the past two decades, this increase has not been linear. Instead, there has been a notably sharp increase since 2015 across many disciplines (Figure 1g, solid lines). Moreover, this sharp increase applies to not only computer science but also wide-ranging disciplines, including, for example, biology, chemistry, and material sciences (Figure 1h). To better understand whether the recent rise of AI's direct impacts on science is driven by changes in AI capabilities or field-specific research directions, we calculate counterfactual AI impact scores by holding AI n-grams constant in 2015. We find that the counterfactual scores (Figure 1g, dashed lines) deviate substantially from the AI impact scores measured from data, which indicates that, across disciplines, sciences benefit disproportionately more from cutting-edge AI capabilities and advances. Overall, these results suggest that new AI capabilities play an important role in contributing to AI's growing impacts on scientific research (see Supplementary Note 4 for results on unpacking AI's growing impacts).

### The potential impact of AI

While explicit mentions of AI terms in research papers signal the direct use of AI, AI may also exert potential impacts on scientific research beyond direct uses. In particular, the growing AI capabilities may help perform some core tasks that a research field demands. The literature suggests that AI capabilities and field tasks can be captured by verb-noun pairs (e.g., "learn representation")<sup>57-59</sup>, prompting us to develop an "AI capability-field task framework" to estimate

the potential impact of AI on research (**Figure 2a**). We apply NLP algorithms to extract verb-noun pairs from the titles of both AI papers and patents to estimate AI capabilities<sup>70-72</sup> (see Methods for details). Taking biology as an example, our framework suggests that the subfield that features the largest potential AI impact is called biological system (**Figure 2c**), as many of its core tasks appear aligned with inferred AI capabilities (e.g., "extract feature," "predict property," "improve prediction," and "model dynamic"). Interestingly, the biological system field, ranked 5<sup>th</sup> among all non-computer science fields (**Figure 2d**), also happens to be the field of the AlphaFold paper<sup>33</sup>, which was deemed as Science's breakthrough of the year 2021. Applied systematically to all fields and disciplines, the developed framework allows us to estimate and infer which disciplines or subfields within each discipline might benefit the most from AI.

While sciences differ in their direct use of AI (Figure 1h), we find that the differences in the potential impact of AI scores are relatively small across the disciplines (Supplementary Figure S8), suggesting the potentially widespread applicability of AI in science. The discrepancy between potential and direct AI impact scores is especially strong in such fields as nuclear engineering, biotechnology, petrology, inorganic chemistry, and business administration. We further zoom into within-discipline heterogeneity, plotting the ranking percentiles of each discipline's subfields based on their direct and potential AI impact scores, respectively. We find that the two ranking percentiles are indeed correlated with each other (Figure 2e), especially among the top-ranked subfields (Figure 2f). Notably, almost every discipline has some subfields with substantially large AI impact scores (Figure 2g), which holds robust even for disciplines with an overall small AI impact score, such as chemistry and business. Overall, these results suggest that the impact of AI on scientific research appears pervasive across disciplines, and its potential impact may extend beyond its current uses in science.

#### Growing knowledge demands for AI

The rapidly expanding AI frontier and its growing impacts on science may pose growing knowledge demands for AI expertise on domain researchers, raising the question of whether the education and training of AI skills are commensurate with AI's impacts. To answer this question, we analyze 4.6 million university course syllabi from the Open Syllabus Project (OSP) database<sup>73</sup> and estimate the level of AI education in each discipline (see Methods and Supplementary Note 5 for details). We find that, excluding the top three computational disciplines (i.e., computer science, mathematics, and engineering), there is a remarkable lack of correlation between AI education level and AI's impact on the disciplines, which holds robust for both direct use and potential benefits estimated using our frameworks (Pearson's r = 0.325 and P-value = 0.256 for the direct impact; Pearson's r = 0.281 and *P*-value = 0.331 for the potential impact; Figure 3ab). These results are robust using alternative measures of AI education levels (see Supplementary Note 5 for details). We further repeat our analyses at the field level, for undergraduate courses, and across different time periods, yielding similar conclusions (Supplementary Figure S11). Taken together, these results suggest that the supply of AI talents in most scientific disciplines appears to be incommensurate with the benefits these disciplines may extract from AI capabilities.

To meet the growing knowledge demands on AI, domain experts may rely on cross-discipline collaborations to access AI capabilities. We analyze collaboration patterns for AI-related papers co-authored by domain experts and/or computer scientists (see Methods and Supplementary Note 5 for details). We find that about half of AI-related papers are solely published by domain experts, and only a quarter are collaborative works (**Figure 3c**). Disciplines that see more impacts of AI show a larger propensity to collaborate with computer scientists (Pearson's r = 0.835 and *P*-value < 0.001 for the direct impact; Pearson's r = 0.813 and *P*-value < 0.001 for the potential impact; **Figure 3de**). Further, there is an increasing share of collaborative AI-related papers in several

major disciplines, especially in recent years (**Figure 3f**), suggesting that there is a growing reliance on AI expertise by domain experts (Supplementary Figure S12). The results highlight the importance of teamwork and cross-domain collaborations amidst AI's potentially increasing impacts on scientific research and the narrowing of individual expertise across the sciences<sup>74</sup>.

#### **Demographic disparities**

As the connection between AI and scientific research deepens, it is important to understand who benefits from AI, which has implications for the equity and sustainability of the research enterprise. Here we study the gender and race/ethnicity composition of each discipline and further examine whether the benefits from AI may be distributed differently across demographic groups. Specifically, we leverage the Survey of Doctorate Recipients (SDR) data to solicit information on U.S.-residing employed doctoral scientists and engineers by the discipline of doctorate, gender, and race/ethnicity. We then crosswalked the SDR fields of doctorate to the MAG disciplines and calculated the share of female scientists and underrepresented minorities (URM) scientists in each discipline, respectively (see Methods and Supplementary Note 7 for details).

We find a negative correlation between the share of female scientists and the AI impact score for both the direct use (Pearson's r = -0.495; *P*-value = 0.060; **Figure 4a**) and the potential impact (Pearson's r = -0.555; *P*-value = 0.032; **Figure 4b**). Aggregating the AI impact scores of all disciplines by their gender composition, we find that fields with a higher proportion of female scientists tend to be associated with less benefit from AI (**Figure 4cd**). Studying the composition of racial and ethnic groups across disciplines, we find another negative relationship between the share of URM scientists in each discipline and its AI impact score, a pattern that is again robust for both the direct use of AI (Pearson's r = -0.627; *P*-value = 0.012; **Figure 4e**) and its potential impact (Pearson's r = -0.667; *P*-value = 0.007; **Figure 4f**) and appears especially strongly for black scientists within the URM scientists (**Figure 4gh**). Together, these results suggest that, as AI's impact on research grows, potentially bringing substantial benefits to all scientific disciplines, these benefits tend to be distributed unequally across demographic groups. Inadvertently, this unequal effect may further exacerbate the existing inequalities in science<sup>75,76</sup>.

### Discussion

In this study, we develop a quantitative measurement framework to estimate the extent to which AI may benefit scientific research, aiming to quantify both the direct use of AI and the potential impact of AI across a range of scientific disciplines and research fields. We find that scientific disciplines feature an increasing use of AI, growing especially sharply in recent years. Papers that use AI tend to see an impact premium, more likely to be highly cited both within and outside their disciplines. At the same time, there is substantial heterogeneity in AI's impacts across different disciplines, but notably, almost every discipline has some subfields that see great benefits from AI. For example, while the medical discipline as a whole is not ranked among the highest in AI benefits, some of its subfields (e.g., nuclear medicine, radiology, and medical physics) show substantially large AI benefits (see Supplementary Figure S9 for detailed results). Overall, these results suggest that the benefits that AI may bring to scientific research appear widespread across disciplines, potentially extending beyond its current uses in science.

A systematic understanding of AI's impact on scientific research may better inform science and education policy. The uncovered misalignment between AI's impact in a discipline and the education focus on AI to upskill scientists within the discipline has implications for understanding how to best prepare next-generation scientists to fully leverage AI advances. It is also important to recognize that as AI becomes increasingly capable of performing research tasks, it may create unequal impacts on the research workforce. Disparities along various demographic dimensions represent long-standing concerns across the sciences<sup>77-81</sup>. Our analysis reveals potential new sources of inequality through AI's benefits for science, which has implications for building and promoting a diverse, equitable, and inclusive research workforce.

While this study takes an initial step in assessing how AI might impact scientific research, there are limitations that are important to consider when interpreting the results. First, our analyses build on the future of work literature and rely on publication and patent data. Given its multidimensional nature, however, the benefit of AI for science may go beyond what can be estimated from such datasets, suggesting that the frameworks may underestimate the full range of benefits that AI may bring to research. For example, AI may optimize the research process by powering new tools and systems that improve the efficiency of doing science, including improving access to information, reducing the knowledge burden, guiding human intuition, automating routine research tasks, and more<sup>82,83</sup>. Second, AI research evolves rapidly, suggesting the need for continuous monitoring and updates for the estimates of its benefits to science. For example, our datasets trace publications and patents to the end of 2019 hence cannot fully capture the recent rise of foundation models in AI research<sup>84,85</sup>. Given that foundation models, such as large language models, can be adapted to a wide range of downstream tasks through fine-tuning, it is conceivable that they may play a significant role in augmenting scientific research. Third, as a general-purpose technology<sup>86,87</sup>, AI may generate downstream spillover effects, creating indirect impacts on various domains. For example, by discovering faster matrix multiplication algorithms<sup>88</sup>, AI may create further indirect impacts on disciplines that would benefit from such advances. Fourth, although directly mentioning AI-related terms in publications is suggestive of using AI in research, the same term may have different meanings, and there are other ways to define AI-related terms<sup>48</sup>. Thus, a deeper understanding of how AI is used across the sciences and an improved identification of AI research and new AI capabilities represent important areas for future research. Lastly, as the capabilities of AI continue to grow and science becomes increasingly impacted by AI, it will be ever more critical to understand the fairness and equity of AI in research<sup>13,89</sup>.

Overall, these findings based on large-scale quantitative analyses may prove helpful to the AI community, helping us better understand what capability might be the most fruitful for scientific research. At the same time, the misalignment between the education of AI and its impact on research suggests that collaborations between AI researchers and domain experts may be especially fruitful, bridging deep domain expertise with new AI advances. Given that tomorrow's technological developments often begin upstream from basic scientific research<sup>90</sup>, a better understanding of AI's impacts on science may further inform the range of important policy considerations for the future of education, research, and innovation<sup>2-4</sup>.

## Methods

**Data sources.** To estimate the impact of AI on science, we use a variety of datasets that include information regarding scientific publications, patents, course syllabi, and the demographics of researchers (see Supplementary Note 1 for details). We briefly introduce two primary datasets. (1) We use the Microsoft Academic Graph (MAG) database for publication data. We collect information on 87.6 million papers published between 1960 and 2019 of various types ("journal," "conference," "book," or "book chapter"). These papers are categorized into 19 disciplines (e.g., "computer science") and 292 fields (e.g., "machine learning") under the MAG "field of study" taxonomy, in which one discipline contains several child fields (see Supplementary Note 1.1 for details). For each paper, we collect the title, publication year, discipline, and field information. (2) We use PatentsView for patent data. We collect information on 7.1 million patents published between 1976 and 2019 from PatentsView, a data platform based on bulk data from the U.S. Patent and Trademark Office (USPTO). Each patent is associated with a list of patent classification codes and keywords (see Supplementary Note 1.2 for details). Using these codes and keywords, we identify AI-related patents. Together, the MAG publication data and USPTO patent data allow us to estimate AI's direct and potential impacts on each scientific discipline and research field.

We supplement our analysis with two more datasets to examine the alignment of AI's impact with the level of AI education and to study the representativeness of gender and race in science. (1) We use syllabus data that is sourced from the Open Syllabus Project (OSP), the world's first large-scale online database of university course syllabi. Our syllabus dataset contains 4.6 million English-language syllabi published between 2010 and 2019. Each syllabus is associated with a list of CIP academic fields and a list of referenced articles or books<sup>73</sup>. We manually crosswalk CIP codes to MAG fields, and we link syllabus references to MAG publications (see Supplementary Note 5 for details). (2) We use the Survey of Doctorate Recipients (SDR) for demographic data regarding individuals with a U.S. research doctoral degree in a science, engineering, or health field. We use the 2017 SDR data on scientists and engineers, including the discipline of their doctorate, their sex, and their race and ethnicity. We manually crosswalk the SDR doctorate disciplines to the MAG disciplines (see Supplementary Note 7 for details).

Calculation of AI impact scores. We estimate AI's direct impact by implementing the "AI ngram framework." Specifically, following prior studies<sup>67</sup>, we identify AI-related papers by the five MAG fields ("machine learning," "artificial intelligence," "computer vision," "natural language processing," and "pattern recognition"). Identifying AI-related research from publication databases remains a challenging task, and there are other ways to identify AI research (see Supplementary Note 2.1 for details). We extract n-grams (bigrams and trigrams) from the titles of AI-related papers and normalize them by lemmatizing words (e.g., "patterns" -> "pattern") and standardizing them (e.g., "picture" -> "image"). From these normalized n-grams, we filter AIrelated n-grams using a list of topics under the five AI field categories in the MAG "field of study" taxonomy. This taxonomy is constructed primarily based on Wikipedia topics (see Supplementary Note 1.1 for details). We calculate the frequency of AI n-grams per paper to approximate cumulative AI advances. Formally, the frequency vector of AI n-grams at year t is  $\hat{G}_{AI}^t = G_{AI}^t / N_{AI}^t$ , where  $G_{AI}^{t}$  is the vector that summarizes the counts of AI n-grams extracted from AI papers published before year t, and  $N_{AI}^{t}$  is the number of these AI papers. We repeat this process for papers in each MAG field to extract n-grams (both AI and non-AI n-grams) and calculate their frequency to approximate current field development. Formally, the n-gram frequency vector for the biology discipline at year t is  $\hat{G}_B^t = G_B^t / N_B^t$ , where  $G_B^t$  is the vector that summarizes the count of n-grams extracted from biology papers published before year t, and  $N_B^t$  is the number of these biology

papers. Finally, we calculate the direct AI impact score for biology at year *t* by weighting the AI n-grams frequency and the matched n-grams frequency in biology:

$$S_D^t = \sum \widehat{G}_{AI}^t \cdot \widehat{G}_B^t$$
 ,

where the symbol " $\sum$ ." represents dot product among the matched AI and biology n-gram frequencies. A larger direct AI score means the field is more strongly affected by AI.

We estimate the potential impact of AI by implementing the "AI capability-field task framework," which is built on the future of work literature<sup>57-59</sup>. Specifically, we predict the capabilities of AI by extracting verb-noun pairs (e.g., "predict structure") from AI-related paper titles using a dependency parsing algorithm developed in NLP (see Supplementary Note 3.2 for details)<sup>70-72</sup>. After normalizing verb-noun pairs through lemmatization and standardization, we calculate their relative frequency to approximate cumulative AI capabilities in papers. Formally, the AI paper capability frequency vector at year t is  $Paper(\hat{C}_{AI}^t) = C_{AI}^t / \sum C_{AI}^t$ , where  $C_{AI}^t$  is the vector that summarizes the counts of verb-noun pairs extracted from AI papers published before year t. We repeat this process for AI-related patents and calculate the AI capability frequency vector. We normalize the frequency vectors of both AI papers and AI patents to approximate AI capabilities:

$$\hat{C}_{AI}^{t} = \left[Paper(\hat{C}_{AI}^{t}) + Patent(\hat{C}_{AI}^{t})\right]/2,$$

where the symbol "+" represents summing up two frequencies of the same verb-noun pair. Analogously, we predict the basic tasks of a research field (i.e., what the field does) by extracting and normalizing verb-noun pairs from the titles of papers in the field. Taking the biology field as an example, the field task frequency vector at year t is  $\hat{T}_B^t = T_B^t / \sum T_B^t$ , where  $T_B^t$  is the vector that summarizes the counts of verb-noun pairs extracted from biology papers published before year t. Further, we apply the term frequency-inverse document frequency to discount the weight of commonly appearing verb-noun pairs in both AI capability and field tasks frequency vectors (see Supplementary Note 3.3 for details). Finally, we estimate the potential AI impact score of biology at year t by overlapping its current tasks with cumulative AI capabilities:

$$S_P^t = \frac{\sum \hat{C}_{AI}^t \cdot \hat{T}_B^t}{\sum \hat{C}_{AI}^t \cdot \hat{C}_{AI}^t},$$

where the symbol " $\Sigma$ ·" represents dot product among matched AI and biology verb-noun frequencies, and the denominator is applied to compare across different years. A larger potential AI score means the field is predicted to be more strongly affected by AI.

**Estimation of AI education levels.** We measure the level of AI education in each discipline by leveraging OSP syllabus data and MAG publication data. Specifically, the OSP data categorizes course syllabi by educational fields and provides a link from syllabi to their referenced papers. First, we crosswalk taxonomies of educational and research disciplines by manually mapping OSP fields to MAG disciplines. We then match syllabi-referenced papers to MAG publications using DOI (digital object identifier), title, and publication year (see Supplementary Note 5.1 for details). Next, we estimate a discipline's AI education level by calculating the fraction of citations from OSP syllabi in the discipline to AI-related publications among citations to all publications. As robustness checks, we also calculate an alternative measure, which is the fraction of a discipline's syllabi that cites at least one AI publication (see Supplementary Note 5.2 for details on methods and Supplementary Note 5.3 for additional results on robustness checks).

**Calculation of cross-discipline collaborations on AI.** We estimate the level of cross-discipline collaborations on AI-related research between domain experts and AI researchers based on AI papers published in disciplines other than computer science (see Supplementary Note 6.1 for details). Specifically, we first assign a primary discipline to each researcher based on the discipline in which they published most frequently between 1960 and 2019. We then categorize each AI paper published in a discipline into one of four co-authorship types based on the composition of its authors' primary disciplines: (1) "domain & CS," which involves both domain experts and computer scientists; (2) "domain sole," which involves only domain experts; (3) "CS sole," which involves only computer scientists; Next, we calculate the share of collaborative AI papers (i.e., those in the "domain & CS" type) for each discipline (see Supplementary Note 6 for detailed methods).

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# Data availability

The MAG data are available at https://zenodo.org/record/6511057. The USPTO patent data are available at https://patentsview.org. The OSP dataset is available from the paper at https://www.pnas.org/doi/10.1073/pnas.1804247115. The SDR researcher demographic data are available at https://www.nsf.gov/statistics/srvydoctoratework.

## **Code availability**

Data are linked and analyzed with customized code in Python 3 using standard software packages within these programs.

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# **Author contributions**

D.W. supervised the project. J.G. and D.W. conceived the idea. J.G. collected data and performed analyses. J.G. and D.W. analyzed the results, interpreted the findings, and wrote the paper.

## **Competing interest declaration**

The authors declare no competing interests.

## Figures



Figure 1. Measuring the direct impact of AI on scientific research. (a) The "AI n-gram framework" for estimating the direct use or impact of AI. First, AI-related papers are identified by the five AI subfields in the MAG data. Then, n-grams (bigram and trigram) are extracted from the titles of AI papers. Next, the frequency of AI n-grams per paper is calculated after normalization and lemmatization. Similarly, n-grams are extracted for papers in each field, and the frequency of n-grams per paper is calculated. Finally, a field's direct AI impact score in a year is calculated by the sum of the dot product between frequencies of AI ngrams cumulated up to the year and the field's n-grams in the year. (b) The frequency of the top 20 AI ngrams in 2019 and its trend over the past two decades. (c) Temporal changes in the rankings of the top 20 AI n-grams from 2003 to 2019. AI n-grams are colored by their orders in 2018-2019, and exceptions are in gray. (d) The frequency of top 20 AI n-grams in physics, chemistry, and psychology in 2019. The top five AI n-grams are colored, and others are shown in gray. (e) The ratio of the hit rate of AI-using papers over non-AI-using papers. Here AI-using papers are identified by mentioning at least one AI-related term, and the hit rate of papers (Hit) is defined as being in the top 5% by total citations within the same field and year. (f) The ratio of the share of outside-field citations (SOC) for AI-using papers over that for non-AI-using papers. (g) Temporal trends of AI's direct impact on different disciplines. Each discipline uses its y-axis scale to illustrate the relative change best. The dashed line shows the counterfactual score calculated using cumulative AI n-grams fixed in 2015 and each discipline's current n-grams. The percentage change comparing the score with the counterfactual in 2019 is shown. (h) Comparing direct AI impact scores of all disciplines under the same y-axis scale. Curves are colored according to the disciplines in panel (g); for example, dark blue shows computer science, and orange shows engineering.



**Figure 2. Measuring AI's potential impact and the discipline heterogeneity. (a)** The "AI capability-field task framework" for estimating the potential AI impact. First, AI capabilities are inferred by extracting verb-noun pairs from AI-related papers and patents using the dependency parsing algorithm. Then, field tasks are inferred from papers in each field using the same method. Next, the potential AI impact score is calculated by aligning field tasks with AI capability after discounting the weight of common tasks across all fields. (b) The frequency of the top 10 AI verb-noun pairs in 2019 and their temporal trends over the past two decades. (c) Top 10 subfields of biology by the potential AI impact scores in 2019 and their temporal trend in the past two decades. The biological system field is consistently ranked 1<sup>st</sup>. (d) Top 100 fields by the potential AI impact score in 2019. The top 20 non-CS fields are highlighted on the right, where the biological system is ranked 5<sup>th</sup>. (e) The strong correlation between direct and potential AI impact scores of research fields based on their rank percentile. (f) The significant overlap among the top 3 subfields for each discipline by direct and potential AI impact scores. Most disciplines exhibit 2 or 3 overlapped subfields based on the two AI impact scores. (g) The substantial heterogeneity of AI's impact within scientific disciplines. The rank percentiles of each discipline's subfields are shown, where the rankings by the direct AI impact score are in the upper row and by the potential AI impact score in the lower row.



**Figure 3. Misalignment in AI education but growing knowledge demand for AI. (a)** The correlation between the direct AI impact score and the AI education level estimated by the share of syllabus references to AI-related papers. Linear fits with 95% confidence intervals are shown. The red line shows that the correlation loses significance when excluding the top three disciplines: computer science, engineering, and mathematics. (b) The correlation between the potential AI impact score and the AI education level. (c) The treemap chart shows the share of AI papers by four co-authorship types, where "domain & CS" represents collaborative AI papers by both domain experts and computer scientists, "domain sole" represents AI papers by domain experts only, "CS sole" represents AI papers by computer scientists. Here only AI papers outside the computer science discipline are considered. (d) The positive correlation between the direct AI impact score and the share of collaborative AI papers in each discipline. (e) The positive correlation between the potential AI impact score and the share of collaborative AI papers in each discipline. (f) The share of collaborative AI papers are shown, and curves are smoothed by taking a three-year moving average.



**Figure 4. Gender and racial disparities in AI's impact across disciplines. (a)** The negative correlation between the direct AI impact score and the share of female scientists in each discipline. **(b)** The negative correlation between the potential AI impact score and the share of female scientists. **(c)** The average direct AI impact score for female and male scientists, respectively. The score is calculated by weighting the gender share of each discipline by its direct AI impact score. **(d)** The average potential AI score for female and male scientists. The uRM category includes African American or Black, American Indian or Alaska Native, Hispanic or Latino, and Native Hawaiians or other Pacific Islanders. **(f)** The negative correlation between the potential AI impact score for different racial and ethnic groups. The score for each group is calculated by weighting the share of a discipline's scientists in the group by its direct AI impact score. The average score for each racial and ethnic group under the URM category is shown separately on the right. **(h)** The average potential AI impact score for different racial and ethnic groups.