Technical Appendix
Resource Democratization: Is Compute the Binding Constraint on AI Research?

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Sampling Methodology

Top AI Journals and Conferences

We included a journal in our list of top AI conferences and journals if it met either of the following two criteria as of (approximately) March 1, 2022:

1. The conference or journal is tracked by the website CSRankings.org as a top conference or journal in the subfields of artificial intelligence, computer vision, machine learning & data mining, or natural language processing; or
2. The conference or journal has an h5-index over 100 as tracked by Google Scholar in the subfields of artificial intelligence, computational linguistics, computer vision & pattern recognition, data mining & analysis, or robotics.

The final list of included conferences and journals, along with the number of results from each conference or journal is provided in Table 1.

AI roles in LinkedIn profiles

We identified AI researchers working in industry if their LinkedIn profile met either of the following criteria as of (approximately) March 1, 2022:

1. The respondent's current role on LinkedIn was listed as machine learning engineer, machine learning architect, machine learning analyst, machine learning lead, artificial intelligence engineer, artificial intelligence architect, artificial intelligence analyst, or artificial intelligence lead; or
2. The respondent's current employer on LinkedIn was listed as an AI startup included on the CB Insights list of 46 AI startups and the respondent's current role was listed as one of the job titles listed in Table 2 (CBInsights).

Response Rates and Sample Representativeness

Our final response rate of 1.7% reflects other recent web-based surveys of AI researchers and experts, which have reported response rates from 1.1 to 21%, as shown in Table 3. Several of the surveys either offered incentives or had particularly large samples from academia, both of which can increase response rates.

As with most surveys, not all invited participants choose to participate. This raises concerns regarding nonresponse bias, which could occur if respondents differ meaningfully from those who choose not to respond on characteristics relevant to the study. If present, nonresponse bias threatens the validity of conclusions drawn from the survey. It is worth noting, however, that a low response rate does not itself induce nonresponse bias; response rates can be low without meaningful differences between respondents and nonrespondents, while response rates can be high and have meaningful differences between those groups (Groves and Peytcheva 2008).

One way of checking for nonresponse bias is to compare respondents and nonrespondents along known characteristics, which in our survey included each respondent's sector (academia, industry, or government) as indicated either by the domain of their email address or their self-identification within the survey. Table 4 summarizes the total number and sector breakdown of respondents who received, began, and completed the survey. While the final column is based on self-identification within the survey, the first and second columns are based on email domains. Academics were defined as respondents with a ".edu" email address, government respondents as those with a ".mil" or ".gov" email address, and industry respondents as the remainder. If the email failed, bounced, or was blocked before delivery it is not counted. In the case of distribution counts, these emails are based on the Qualtrics distribution report, which excludes seven respondents who only partially completed the survey, and includes respondents who were self screened out by indicating they did not consent to participate in the study. In the survey itself, one respondent selected "None of these" as their primary affiliation and another respondent completed the survey but did not answer this question, so percentages do not add up to 100%.

With respect to sector composition, we do observe a statistically significant difference (χ^2 = 19.96, $p < .001$) between nonrespondents and the sample of researchers who completed the survey. In particular, academics who received our survey were more likely to complete it, while industry respondents were less likely to do so. We are not able to

Table 1: Number of Authors Identified in AI Conferences and Journals

Conference or Journal Name (Abbreviation on CSRankings, if tracked)	Number of Results
AAAI Conference on Artificial Intelligence (AAAI)	5,953
International Joint Conference on Artificial Intelligence (IJCAI)	1,178
IEEE Conference on Computer Vision and Pattern Recognition (CVPR)	5,010
European Conference on Computer Vision (ECCV)	1,189
IEEE International Conference on Computer Vision (ICCV)	2,431
International Conference on Machine Learning (ICML)	2,686
International Conference on Knowledge Discovery and Data Mining (KDD)	2,266
Neural Information Processing Systems (NeurIPS/NIPS)	4,547
Annual Meeting of the Association for Computational Linguistics (ACL)	2,585
Conference on Empirical Methods in Natural Language Processing (EMNLP)	886
North American Chapter of the Association for Computational Linguistics (NAACL)	72
International Conference on Learning Representations	91
IEEE Transactions On Systems, Man And Cybernetics Part B—Cybernetics	0
Expert Systems with Applications	900
IEEE Transactions on Neural Networks and Learning Systems	781
Neurocomputing	548
Applied Soft Computing	242
IEEE Transactions on Pattern Analysis and Machine Intelligence	1,159
IEEE Transactions on Image Processing	881
IEEE International Conference on Robotics and Automation	4,916

Table 2: List of Job Titles Used to Identify AI-Relevant Employees on LinkedIn

Job title	
Advisory Software Engineer	Programmer Analyst
Analyst Programmer	Quantitative Analyst
Analytics Specialist	Research & Development Engineer
Automation Engineer	Research & Development Specialist
Cloud Architect	Research and Development Engineer
Data Analyst	Research and Development Specialist
Data Analytics	Researcher
Data Architect	Scientist
Data Center Operator	SDE
Data Engineer	Software Designer
Data Scientist	Software Developer
Development Engineer	Software Engineer
ETL Developer	Statistical Programmer
Information Analyst	Statistician
Infrastructure Analyst	Technical Architect
Infrastructure Architect	Technical Lead
Infrastructure Engineer	Technical Product Manager
Java Developer	Technical Project Manager
Machine Learning Engineer	Technology Lead

evaluate nonresponse bias in terms of unobservable characteristics, and for other characteristics about which our survey did ask—such as field of study—we are not able to compare the composition of our respondents to the composition of our overall sampling frame. We considered weighting our responses to account for the observed nonresponse bias in terms of sector, but chose not to do so. For Findings 2.1, 2.2, and 2.3, the analysis in question either only included academics or directly compared academics to industry respondents, in which case weighting based on sector would be irrelevant. For Findings 1.1, 1.2, 1.3, and 2.4, academics generally expressed slightly more concern regarding compute; weighting to account for the greater nonresponse rate among industry respondents would therefore make our core results appear even stronger than we present them above.

Subfield Comparisons

Respondents in our survey were asked to indicate whether they worked in the five top-level fields of computer vision, natural language processing (NLP), robotics, reinforcement

Table 3: Response Rates From Recent Surveys of AI Researchers and Experts

Author	Population	Distribution Method	Incentives Offered?	Response Rate
OECD (2023)	"An audience with expertise or knowledge of AI compute"	Online survey; precise distribution unclear	No	N/A
Michael et al. (2022)	Active members of the Association of Computational Linguistics	ACL membership mailing list; in-person ACL events; Twitter; Slack; email distribution	Yes	5%
Ryseff et al. (2022)	Software engineers (Silicon Valley Employees/Alumni of Top CS Universities)	Email distribution; LinkedIn ads; Northrop Grumman AI Academy	No	1.1%
Zhang et al. (2021)	AI researchers with at least two prominent publications	Email distribution	Yes	17%
Aiken, Dunham, and Zwetsloot (2020)	AI PhD graduates with AI-relevant dissertations from top-ranking universities	Email distribution	No	11%
Grace et al. (2018)	Researchers who published at the 2015 NIPS and ICML conferences	Email distribution	Yes	22%

Table 4: Sector of Respondents Who Received, Began, and Completed the Survey

	Composition among researchers who...		
Sector	received an email with the survey link	began the survey	completed the survey
Industry	38% (11,575)	31% (195)	29% (120)
Government	2% (493)	3% (16)	3% (14)
Academia	60% (18,243)	67% (423)	67% (274)
Total	30,311	634	410

learning, and "other." Respondents indicating working in any of these top-level fields were then shown a series of subfields related to the top-level category and asked to indicate if they worked in each of those subfields; a full list of these subfields can be viewed in the survey instrument, below. On average, respondents in each of the five top-level categories indicated working in roughly a quarter of the related subfields independently of the top-level category in question, as shown in Table 6. In addition, the median academic reported working in a total of three subfields (not including the five top-level fields and the final "none of these" option), while the median industry researcher reports working in a total of four subfields. The difference between the median number of subfields indicated by academics as opposed to industry researchers is significant at p = .004 according to a Mann-Whitney U test. However, this difference is likely explained by the fact that more respondents from industry reported working in NLP than academia, and substantially more subfields were presented to respondents in NLP than other fields. Figure 3 shows the number of subfields indicated by industry and academic respondents for each top-level field.

Figure 4 provides some additional insight into the variation among these subfields. Each point in this figure represents one subfield, with the location on the x-axis indicating the average compute expenditure on a researcher's most compute-intensive project reported across all researchers in the subfield, and the location on the y-axis indicating the mean level of concern from researchers that future contributions will be limited by a lack of access to compute. The positive correlation between the two variables further reflects Finding 2.4: that researchers who already use larger quantities of compute tend to report being more concerned about their lack of access to compute. However, Figure 4 also illustrates that researchers across subfields in both computer vision and NLP are fairly tightly clustered together in a high-compute-use and high-concern category, while the subfields of robotics and reinforcement learning exhibit much

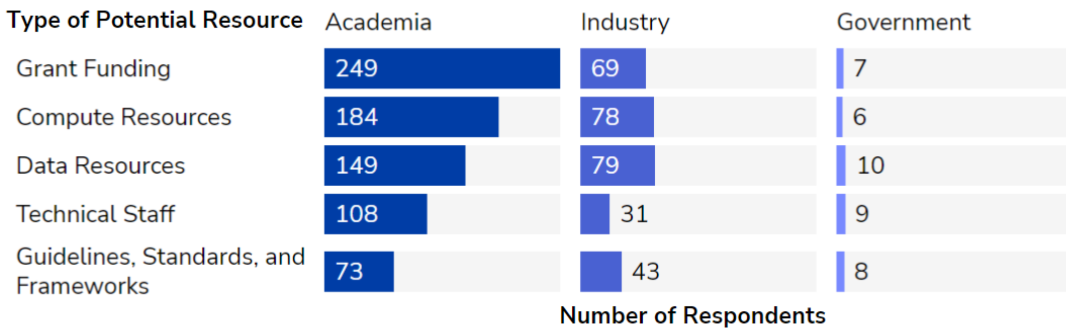

Figure 1: Survey respondent employment sector

Table 5: Survey respondent reported AI fields

	Computer Vision	Natural Language Processing	Reinforcement Learning	Robotics	Other	Total
Academia	95	83	59	58	107	275
Industry	49	58	17	13	47	120
Government	6	2	4	1	6	14

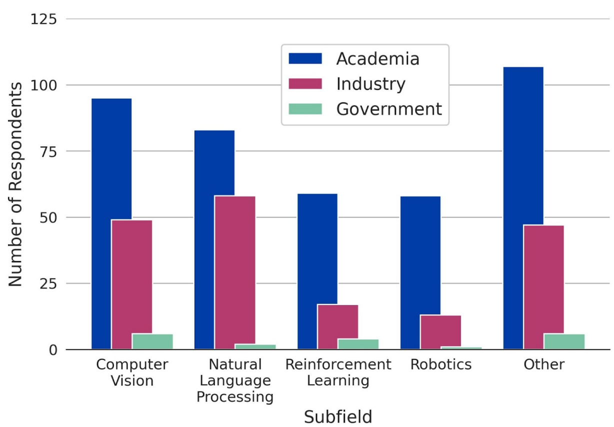

Figure 2: Survey respondent reported AI fields

Table 6: Number and percent of subfield options selected by respondents in each field

Field	Mean Number of Subfields Selected	Number of Subfields Presented	Mean Percent of Subfields Selected
Computer Vision	2.82	10	28%
Robotics	2.74	9	30%
Natural Language Processing	4.22	17	25%
Reinforcement Learning	1.84	8	23%
Other	1.78	7	25%

higher variance. Robotics in particular exhibits significantly less concern that future research will be limited by compute, relative to other subfields. The tight clustering of subfields within NLP may be due to the previously-noted fact that respondents working in NLP indicated, on average, working in a larger number of subfields than in other top-level fields.

Finally, Figure 5 shows that the percent of respondents indicating a desire for government-provisioned compute resources varies substantially by subfield (dotted black lines show the percent across all respondents in a top-level field indicating such a desire). In general, NLP and computer vision researchers are the most likely to indicate support for such resources, and robotics researchers are the least likely. However, there is meaningful variation within computer vision and reinforcement learning in particular, with not all subfields equally interested in using government-provided compute resources.

Model Descriptions

This project's GitHub repository contains the results of a variety of regression models that further analyze our results, as well as the code used to perform all data analysis and significance testing (but not the data, for privacy reasons).

The first two models included are ordinal logistic regressions that delve further into comparisons of compute use across subgroups, specifically focusing on AI fields and industry vs. academia. Model 1 suggests that computer vision researchers and NLP researchers are likely to report higher GPU usage for their most compute-intensive project

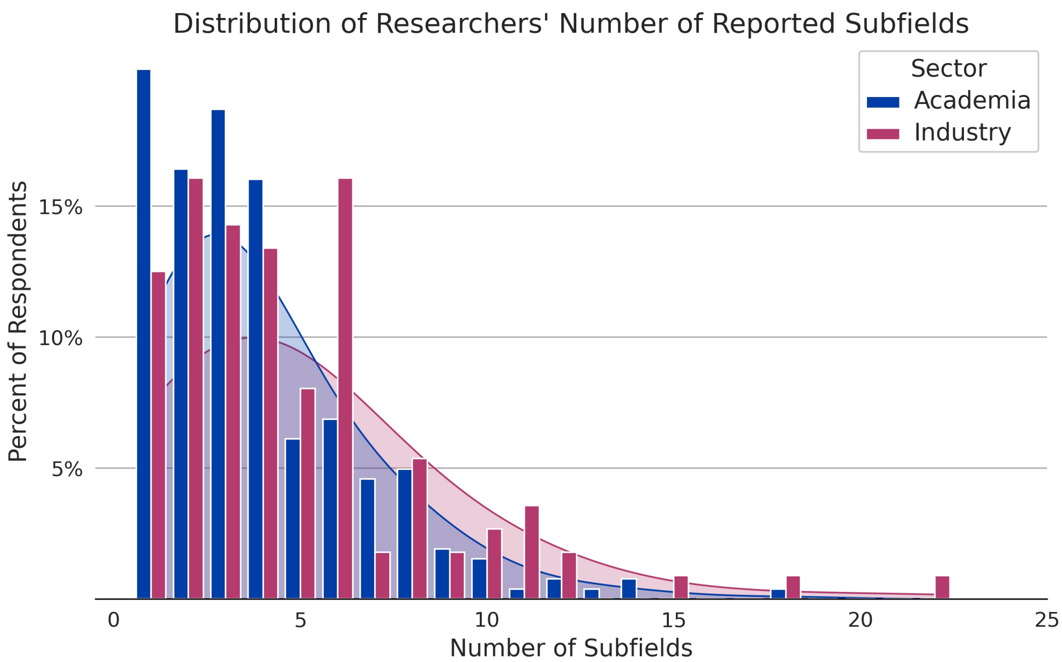

Figure 3: Number of subfields selected by researchers by sector

than other types of researchers ($p < .001$ and $p = .032$, respectively) after adjusting for differences across sectors. There are significantly more NLP researchers in industry in this sample than in academia (see Figure 2, above), so differences between fields could explain the slight difference between industry and academia for GPU hours. However, Model 2 shows that even after accounting for differences in AI field, industry researchers report significantly higher compute usage in monetary terms ($p < .001$).

Since we found significant differences in the field makeup of respondents from academia and those from industry, we also want to examine differences in level of concern that may exist at the field level. Model 3 in this project's GitHub repository addresses this with an ordinal logistic regression of level of concern on sector, research field, and the interaction between sector and research field. This model does not identify significant differences between academics' level of concern about their access to compute and that of industry researchers, even when taking field into account.

Models 4 and 5 further consider the relationship between respondent level of concern about future compute access and compute use in GPU hours for respondents' most compute-intensive project. To do this, they use ordinal logistic regression to model respondents' level of concern about compute access as a function of GPU usage for respondents' most compute-intensive project and the interaction between these two variables (where Model 4 specifies GPU utilization as a categorical variable and Model 5 specifies it as a linear variable). Neither of these is perfectly appropriate – GPU utilization is ordinal. While both models identify a significant positive correlation between GPU usage and stated concern about future contributions, neither model detects a significant impact of sector, either alone or in interaction with GPU usage.

Further Data Analysis and Testing

To further validate our conclusions in Finding 2.4, we performed a number of additional comparisons; these results are found below.

Respondents who reported using greater amounts of compute in their most compute-intensive project also tended to give higher responses on each of the following indicators:

- Frequency of abandoning projects due to insufficient compute ($\rho = .10$)
- Frequency of revising projects due to insufficient compute ($\rho = .28$)
- Frequency of rejecting projects due to insufficient compute ($\rho = .28$)
- Importance assigned to a lack of compute as a reason to consider leaving academia ($\rho = .33$)
- Level of agreement that compute was a major driver of AI progress over the last decade ($\rho = .19$)
- Level of agreement that compute will be a major driver of AI progress over the next decade ($\rho = .16$)

Box 1: Correlation between reported compute usage and compute attitudes and behaviors

We report Spearman's rank correlation. The p-values for the six indicators discussed here were .057, $<.001$, <0.001, $<.001$, .001, and .008, respectively. These values were calculated based on a permutation test with 10,000 samples.

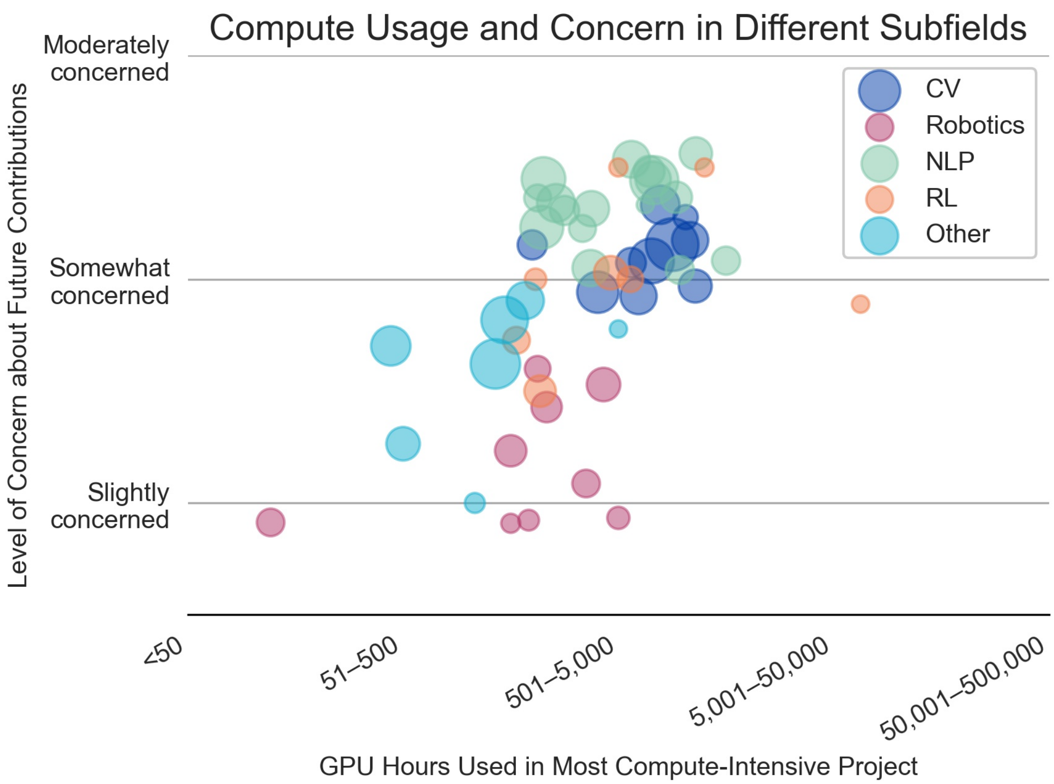

Figure 4: Mean compute use and concern over future compute across subfields

The correlation between compute use and importance assigned to a lack of compute as a reason to consider leaving academia includes only responses from academics; all other correlations include respondents from all sectors.

Survey Questions

The survey was developed using the Qualtrics survey platform, which allows for the use of complex survey logic, including block randomization, conditional questions, answer randomization. We have attempted to reproduce it below, with explanations of the survey logic included as much as possible.

Survey

As a professional employed at a US organization with a job related to artificial intelligence (AI) or a researcher with a recent AI-related publication, [our institutions] invite you to take part in a research study. Our goal is to better understand the needs of AI professionals to achieve research progress. The research findings will inform [our institutions'] publications and policy recommendations on research funding and support offerings. Your participation is completely voluntary and involves an online survey that can be completed in 10-15 minutes. You may choose not to participate by clicking NO below. If you decide not to participate or cease participation, you will not be penalized. There are no known risks or direct benefits from participating in this research. Any publications using the survey responses will maximize confidentiality and report only anonymous, aggregated responses. If you have any questions related to the survey, please contact [removed]. Your consent indicates that you are at least 18 years of age, have read the above information, and voluntarily agree to participate.

- Yes
- No

Survey ends for anyone who answered no.

Roughly what amount of your time at work involves working on AI systems? By AI system, we mean a machine-based system that can (for a given set of human-defined objectives) make predictions, recommendations, or decisions influencing real or virtual environments. By work on AI systems, we mean build, develop, study, or maintain AI systems.

- None of my time
- Some of my time
- A moderate amount of my time
- Almost all of my time
- All of my time

Survey ends for anyone who answered none of my time.

End of Block: Screener

Start of Block: AI research time

How long have you been working on AI systems?

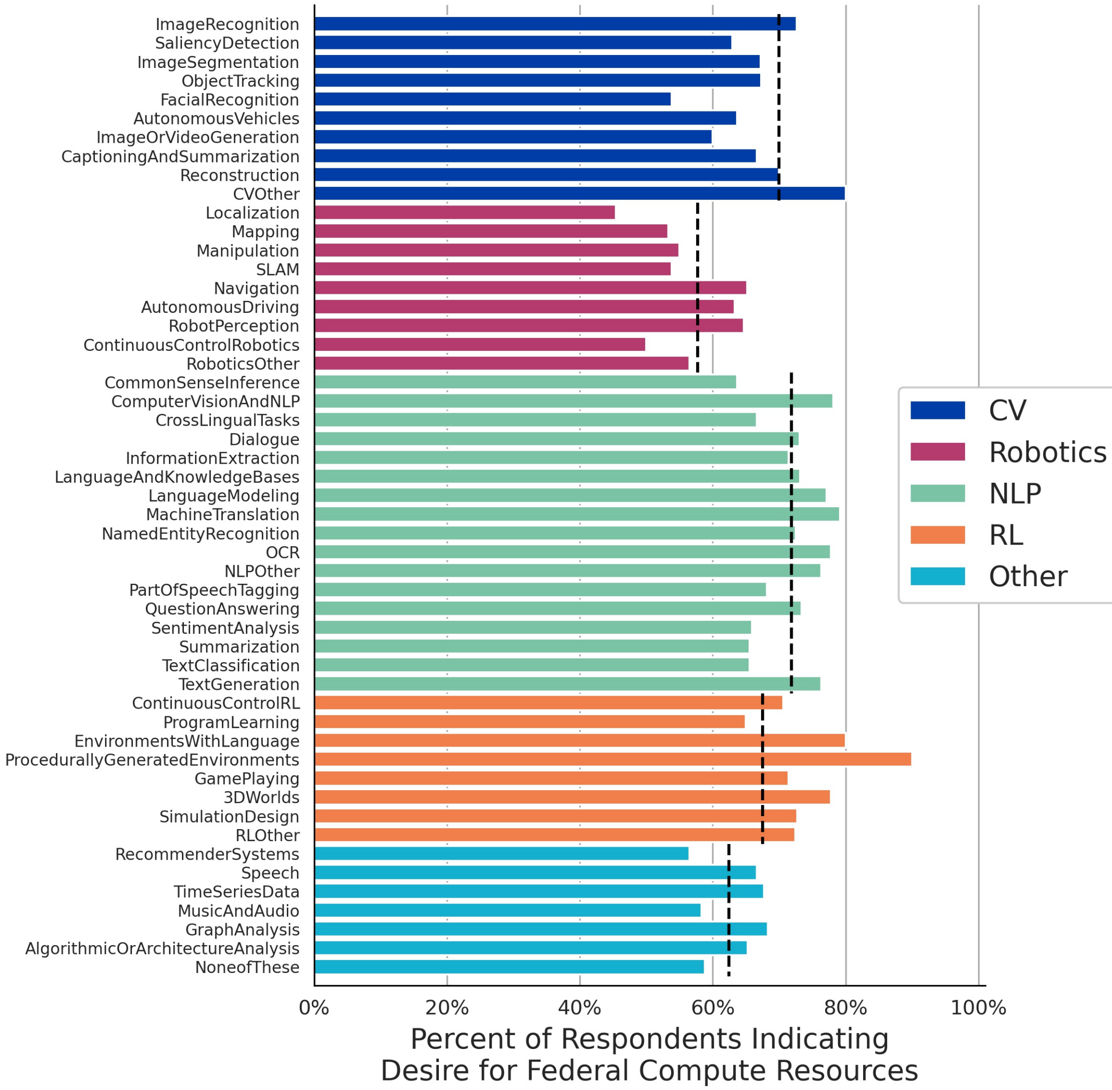

Figure 5: Percent of respondents indicating a desire for government-provided compute by subfield

- Less than one year
- 1 - 5 years
- 6 - 10 years
- More than 10 years

Roughly, what percentage of your time working on AI systems is spent managing compute resources? By managing compute resources, we mean work performed to maintain a computing infrastructure, as opposed to utilizing that infrastructure to work on AI systems.

- 0 - 25%
- 26 - 50%
- 51 - 75%
- 76 - 100%

In the past year, where were the compute resources for your work on AI systems located? Select all that apply.

- Cloud
- On-premise
- I don't know

In the past year, how did you pay for the compute resources you used in your work on AI systems? Select all that apply.

- I used free compute resources
- I paid using personal funds
- I paid using outside funding, not from my employer
- My employer paid
- I don't know

IF In the past year, how did you pay for the compute resources you used in your work on AI systems?... = I paid using personal funds

THEN display this question:

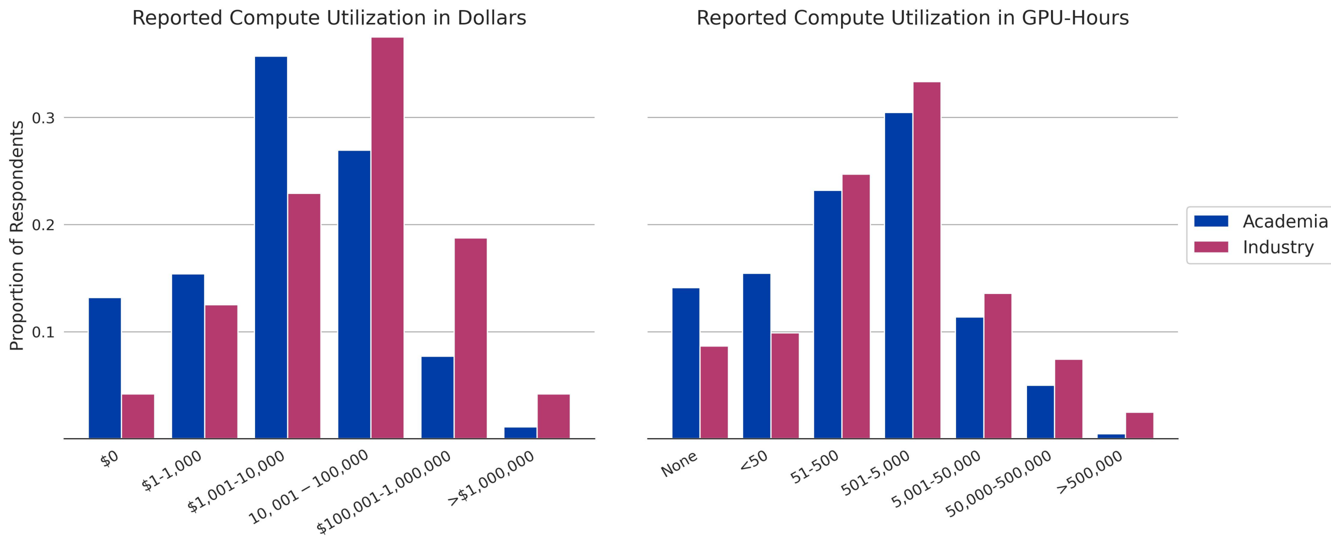

Figure 6: Reported compute Use in cost and GPU-hours for respondents' most compute-intensive projects

In the past year, roughly how much money did you spend in personal funds on compute resources for your work on AI systems?

- Less than $100
- $101–500
- $501–1,000
- $1,001–5,000
- More than $5,000

For a typical AI project that you might work on, how many processors (CPUs, GPUs, TPUs) would you distribute your data or models across?

- 1 processor
- 2-8 processors
- 9-100 processors
- More than 100 processors

For the next set of questions, think of your most significant research project of the last 5 years. By 'significant' we mean a project that contributed the most to progress in your AI-related field. If you did not participate in a research project within the last 5 years that meets this criteria, select N/A below. Otherwise continue onto the next page.

- N/A

Skip to end of block if: For the next set of questions, think of your most significant research project of the last 5 year... = N/A

About how many people worked directly on this project?

- 1
- 2 - 5
- 6 - 15
- 16 - 50
- More than 50

In what year was the project completed?

- 2017
- 2018
- 2019
- 2020
- 2021
- 2022
- Project is ongoing
- I don't know

Which part of this project required the most compute?

- Design
- Data collection or processing
- Training
- Testing and evaluation
- Deployment
- Maintenance

About how much did compute cost in this project, to date?

- $0
- $1 - $1,000
- $1,001 - $10,000
- $10,001 - $100,000
- $100,001 - $1,000,000
- More than $1,000,000
- I don't know

About how many GPU-hours were required for this project, to date?

- None
- Fewer than 50
- 51–500
- 501–5,000
- 5,001–50,000

- 50,001–500,000
- More than 500,000
- I don't know

How important were the following factors to the project? [This question was structured as a matrix]
Importance scale for matrix:

- Not at all important
- Slightly important
- Moderately important
- Very important
- Extremely important

Questions for matrix:

- Unique data
- Size of team
- Specialized knowledge, talent, or skills
- Large amounts of compute

End of Block: Significant Project
Start of Block: Project Check
Next, think of the research project that you participated in over the past five years which required the most compute resources, compared to other projects you participated in during that time.
Display this question if For the next set of questions, think of your most significant research project of the last 5 year... != N/A
Is this the same project you described in the previous questions?

- Yes
- No

End of Block: Project Check
Start of Block: Compute Project
About how many people worked directly on this project?

- 1
- 2 - 5
- 6 - 15
- 16 - 50
- More than 50

In what year was the project completed?

- 2017
- 2018
- 2019
- 2020
- 2021
- 2022
- Project is ongoing
- I don't know

Which part of this project required the most compute?

- Design
- Data collection or processing
- Training
- Testing and evaluation
- Deployment
- Maintenance

About how much did compute cost in this project, to date?

- $0
- $1 - $1,000
- $1,001 - $10,000
- $10,001 - $100,000
- $100,001 - $1,000,000
- More than $1,000,000
- I don't know

About how many GPU-hours were required for this project, to date?

- None
- Fewer than 50
- 51–500
- 501–5,000
- 5,001–50,000
- 50,001–500,000
- More than 500,000
- I don't know

End of Block: Compute Project
Start of Block: General
Now we'd like to ask you to think not about specific projects, but about your work as a whole and the AI field in general.
If the budget for your current or most recent AI project doubled, what would your first priority be?

- Collecting more data
- Refining or cleaning data
- Purchasing more or higher-quality compute
- Hiring more programmers or engineers
- Hiring researchers
- Doing more evaluation or testing

How much compute do you need for AI projects today, relative to 2 years ago?

- Much less
- Somewhat less
- About the same
- Somewhat more
- Much more

How much compute do you have access to for AI projects today, relative to 2 years ago?

- Much less
- Somewhat less
- About the same
- Somewhat more
- Much more

Now we'd like to ask some questions about compute, data, and researcher availability.

[The next three questions were all structured as a matrix, using the same frequency scale]

Frequency scale:

- Never
- Rarely
- Sometimes
- Often
- All the time

In the last two years, how often have you done the following:

- Rejected a project because of insufficient compute.
- Revised an ongoing project because of insufficient compute.
- Abandoned an ongoing project because of insufficient compute.

In the last two years, how often have you done the following:

- Rejected a project due to insufficient data.
- Revised an ongoing project plan due to insufficient data.
- Abandoned an ongoing project due to insufficient data.

In the last two years, how often have you done the following:

- Rejected a project due to insufficient researcher availability.
- Revised an ongoing project plan due to insufficient researcher availability.
- Abandoned an ongoing project due to insufficient researcher availability.

Please indicate your level of agreement with the following statements.

[The next two questions are structured as a matrix, using the same frequency scale]

Frequency scale:

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Progress in AI over the past decade was the result of...

- More or better data.
- More compute.
- Better algorithms.
- More researchers in the field.
- Greater support for AI projects.

Progress in AI over the next decade will be the result of...

- More or better data.
- More compute.
- Better algorithms.
- More researchers in the field.
- Greater support for AI projects.

How concerned are you, if at all, that a lack of compute resources will be an obstacle to your contributions to AI in the next decade?

- Not at all concerned
- Slightly concerned
- Somewhat concerned
- Moderately concerned
- Extremely concerned

End of Block: Future AI

Start of Block: Gov Resources

The U.S. government is exploring creating a national AI research resource, which could provide various types of support to AI researchers. Which government-provided resources would you find useful? Please select all that apply.

- Data resources
- Compute resources
- Technical staff (e.g., research programmers, administrative support)
- Grant funding
- Guidelines, standards, and frameworks

If you have any other thoughts or suggestions about the U.S. government creating national AI research resources, please detail them below.

[Optional open-ended response available here]

In what sector is your primary professional affiliation?

- Academia
- Industry
- Government
- None of the Above

Display this question if In what sector is your primary professional affiliation? = Academia

Have you ever considered leaving academia for an AI-related job in industry?

- Yes
- No

Display this question if Have you ever considered leaving academia for an AI-related job in industry? = Yes

[This question is structured as a matrix using an importance scale]

Scale:

- Not at all important
- Slightly important
- Moderately important
- Very important
- Extremely important

How important were the following factors in motivating your consideration to leave academia?

- Salary and/or benefits.
- Lack of sufficient data resources in academia.

- Lack of sufficient compute resources in academia.
- Ability to work on interesting projects.
- Ability to contribute more meaningfully to AI research.

Display this question if In what sector is your primary professional affiliation? != Academia

Roughly how large is your institution?

- Less than 50 employees
- 50 - 100 employees
- 101 - 500 employees
- More than 500 employees

What is your highest level of education?

- Less than high school
- High school graduate
- Some college
- Associate's degree
- Bachelor's degree
- Master's or other professional degree
- Doctorate

Which subfield(s) of AI is most of your current work in? Please select all that apply.

- Computer Vision
- Robotics
- Natural Language Processing
- Reinforcement Learning
- Other

Display this question if Which subfield(s) of AI is most of your current work in? Please select all that apply. = Computer Vision

What topics do you work on in Computer Vision?

- Image recognition
- Saliency detection
- Image segmentation
- Object tracking and/or re-identification
- Facial recognition
- Autonomous vehicles
- Image or video generation
- Captioning and summarization
- Reconstruction
- Other

Display this question if Which subfield(s) of AI is most of your current work in? Please select all that apply. = Robotics

What topics do you work on in Robotics?

- Localization
- Mapping
- Manipulation
- Simultaneous localization and mapping (SLAM)
- Navigation
- Autonomous driving
- Robot perception
- Continuous control
- Other

Display this question if Which subfield(s) of AI is most of your current work in? Please select all that apply. = Natural Language Processing

What topics do you work on in Natural Language Processing?

- Common sense inference
- Computer vision and NLP
- Cross-lingual tasks
- Dialogue
- Information extraction
- Language and knowledge bases
- Language modeling
- Machine translation
- Named entity recognition
- Optical character recognition (OCR)
- Other
- Part-of-speech tagging
- Question answering
- Sentiment analysis
- Summarization
- Text classification
- Text generation

Display this question if Which subfield(s) of AI is most of your current work in? Please select all that apply. = Reinforcement Learning

What subtopics do you work on in Reinforcement Learning?

- Continuous control
- Program learning
- Environments with language
- Procedurally generated environments
- Game-playing
- 3D worlds
- Simulation Design
- Other

Display this question if Which subfield(s) of AI is most of your current work in? Please select all that apply. = Other

Do you work on any of the following other AI topics? Select all that apply.

- Recommender systems
- Speech
- Time series data
- Music and audio
- Graph analysis
- Algorithmic or architecture analysis
- None of these

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