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# Chapter 4: The Economy

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# Introduction

This chapter is broken into three sections: Jobs, Investment Activity, and Corporate Activity.

The first section on AI Jobs shows data relating to AI jobs, hiring, and skill levels around the globe as well as in US regions. It includes the AI Hiring Index across countries, sectoral demand for AI jobs, and skill penetration of AI by countries, sector, and gender. The section concludes with trends in skill penetration and labor demand for AI jobs from a sub-regional US perspective. The data on AI hiring, skill penetration by gender and sector are drawn from the LinkedIn Economic Graph. The information about online AI job postings for the US by states and metropolitan areas are based on data from Burning Glass Technologies. According to our sources, there has been a rapid increase in hiring for all categories of AI jobs over the past three years, but they remain a small share of total jobs.
The second section on Investment presents startup investment trends for the world, by countries, and by sectors. The data is sourced to CAPIQ, Crunchbase, and Quid. This is followed by trends in Corporate Investment that includes global AI investment activity by investment types: private startup investment, Mergers & Acquisitions (M&A), Initial Public Offering (IPO), and Minority Stake investments. Finally, public investment trends from the US are presented based on data from BloombergGOV.

The third section on Corporate Activity includes data on adoption of AI capabilities in industry, drawing from McKinsey's Global AI survey. This section also presents global trends in robot installations across countries, drawing from data collected by the International Federation of Robotics (IFR).

## Global Hiring

Which countries are experiencing the fastest growth in AI hiring? The hiring rate has been increasing across all the sampled countries, especially for many emerging markets, not just advanced economies.[7] The chart below presents the AI Hiring Index, which is calculated as the percentage of LinkedIn members who had any AI skills (see Appendix for AI Hiring Index definition and Appendix box for the AI skill grouping) on their profile and added a new employer to their profile in the same year the new job began (Figure 4.1.1). The AI hiring rate is normalized for the different countries by dividing over the total number of LinkedIn members in the country. The growth rate is indexed against the average annual hiring in 2015-16; for example, an index of 3 for Singapore in 2019 indicates that the AI hiring rate is 3 times higher in 2019 than the average in 2015-16. The chart shows that the countries with the highest growth in AI hiring on LinkedIn include Singapore, Brazil, Australia, Canada and India.[8] The rapid growth in AI hiring is also confirmed by job postings data from Burning Glass that shows the share of AI jobs (% of total jobs posted online) grew from 0.1% in 2012 to 1.7% in 2019 for Singapore (see Appendix Graph). Similarly, in the US the share of AI jobs grew from 0.3% in 2012 to 0.8% of total jobs posted in 2019. The next section shows the growing role of AI jobs in the US by AI clusters and then economic sectors.

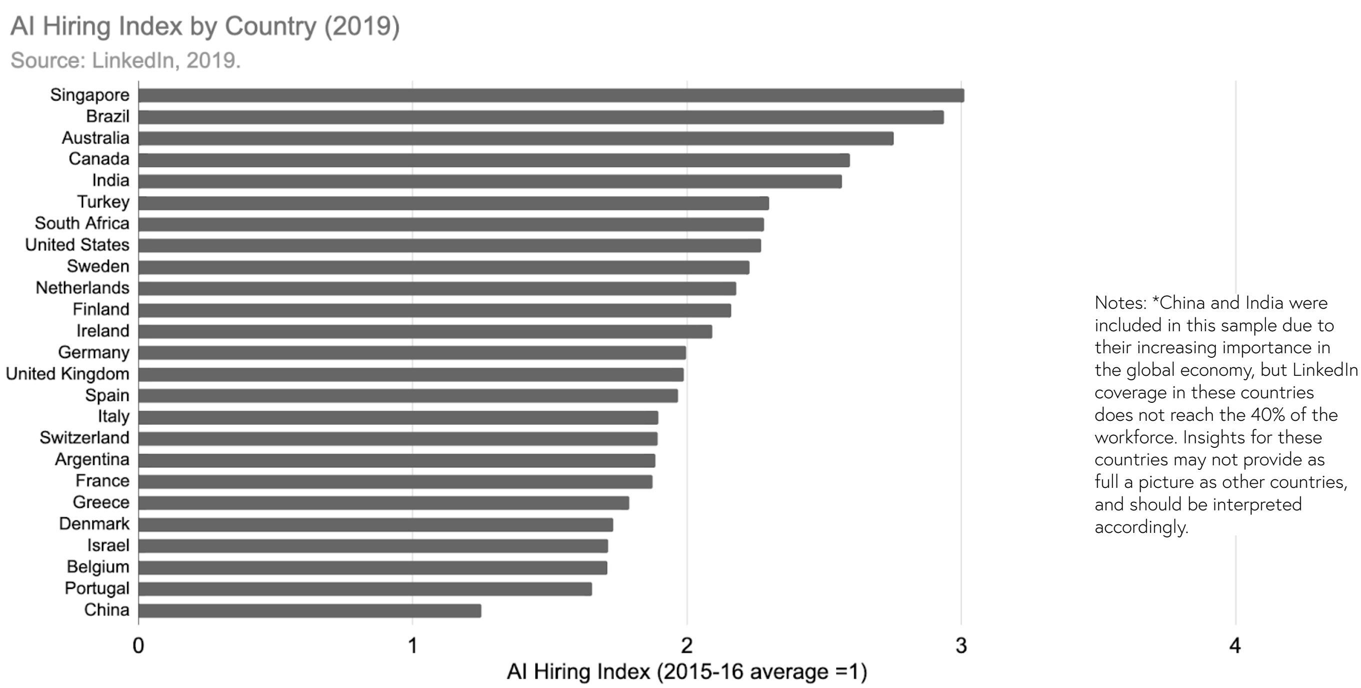



Fig. 4.1.1.

*"Right now the conversation around AI's impact on individual jobs, and the economy more broadly, is dominated by intensely hyped and alarmist commentary. These discussions need to be grounded in facts and measurement, and this report will hopefully contribute to a more thoughtful, reality-based discussion on trends that could drive big impact in the coming decades."*
Guy Berger, Principal Economist at LinkedIn, 2019

[7] Two filters were applied for the countries to be included: 1) countries must have sufficient labor force coverage by our data sources (roughly >40%); and 2) they must have at least 10 AI talents in any given month. Countries and regions with significant representation of their workforce on LinkedIn included in this analysis are United States, Netherlands, Ireland, Denmark, Australia, United Kingdom, Luxembourg, Canada, Singapore, Belgium, New Zealand, Norway, Sweden, United Arab Emirates, France, Portugal, Switzerland, Chile, Spain, Italy, Hong Kong (SAR), Finland, Israel, Costa Rica, Brazil. China and India were included in this sample due to their increasing importance in the global economy, but LinkedIn coverage in these countries does not reach the 40% of the workforce. Insights for these countries may not provide as full a picture as other countries, and should be interpreted accordingly. More generally, LinkedIn's Hiring Rate tracks hires or job switches on LinkedIn; this measure has a strong track record in the US tracking government data on job openings (JOLTS) and core capital goods orders (LinkedIn's Economic Graph, 2019).
[8] It should be noted that the analysis depends on the representativeness of LinkedIn users across countries.

## US Labor Demand by Job Cluster

Is AI labor demand gaining significance in total jobs posted on the web in the US? Which type of AI jobs witnessed the fastest growth in online job postings in the US? The different clusters of AI job postings from the US are presented by month (Figure 4.1.2). These are mutually exclusive and independent skill clusters for AI jobs. The Appendix provides a graph on total number of jobs by skill clusters and a table, which shows the list of AI skill clusters. Machine Learning jobs increased from 0.07% of total jobs posted in the US in 2010 to over 0.51% in October, 2019, Other important categories of jobs include Artificial Intelligence (0.28%), Neural networks (0.13%), NLP (0.12%), Robotics (0.11%), and Visual Image Recognition (0.10%). The Appendix also provides a breakdown of jobs by AI clusters from Indeed.

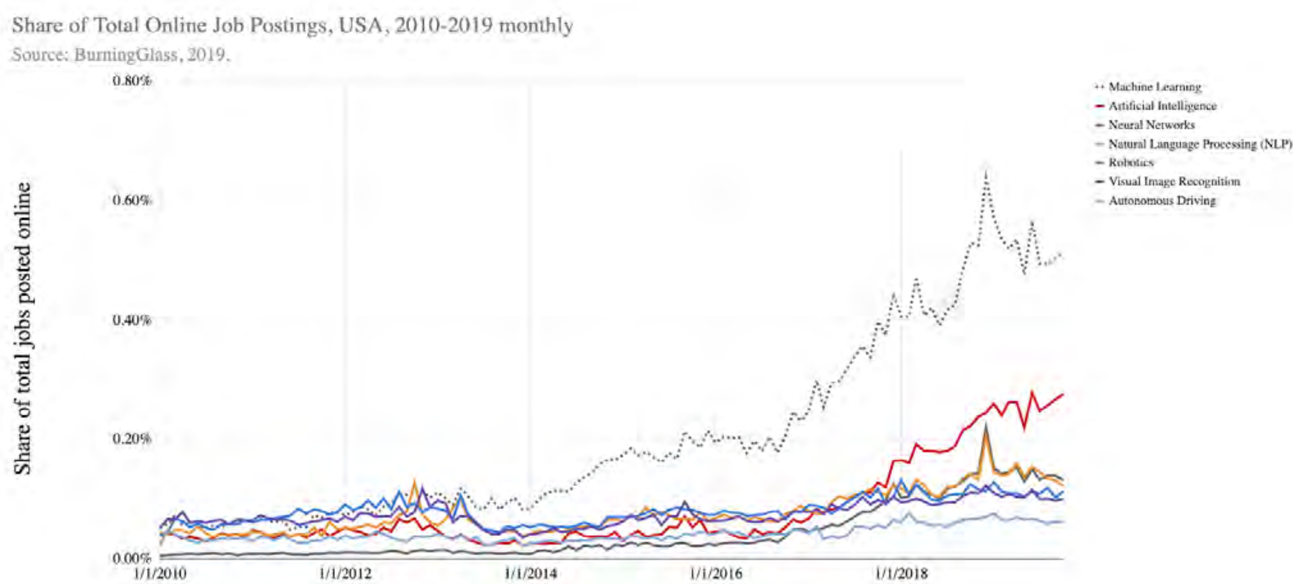



Fig. 4.1.2.

**Machine Learning jobs increased from 0.07% in 2010 to over 0.51% in October, 2019 of total jobs posted in the US, followed by Artificial Intelligence jobs (0.28%), Neural networks (0.13%), NLP (0.12%), Robotics (0.11%), and Visual Image Recognition (0.10%).**

## US Labor Demand By Sector

Which sectors in the US labor market are experiencing stronger AI diffusion via AI job demand? Among sectors, tech, service sectors and manufacturing show the greatest rise in demand for AI skills. The charts below plot the number of AI jobs posted as a percentage of the total jobs posted by sectors in the US. The first provides the ranking of industries with highest demand (percent of total jobs posted) in 2019 (Figure 4.1.3); while the second chart provides a time-series view for the individual sectors (Figure 4.1.4).

Tech service sectors like Information have the highest proportion of AI jobs posted (2.3% of the total jobs posted), followed by Professional, Scientific and Technical Services (over 2%), Finance and Insurance (1.3%), Manufacturing (1.1%), and Management of companies (0.7%). The demand for AI jobs has increased across all economic sectors. The proportion of AI jobs posted across Information, Professional, Scientific and Technical, Finance and Insurance, Administrative and Waste Management has increased by over one percentage point (in terms of share of total jobs posted). On the other hand, the traditional services sector, which includes construction, arts, public administration, healthcare and social assistance, demonstrates a relatively lower demand for AI jobs.

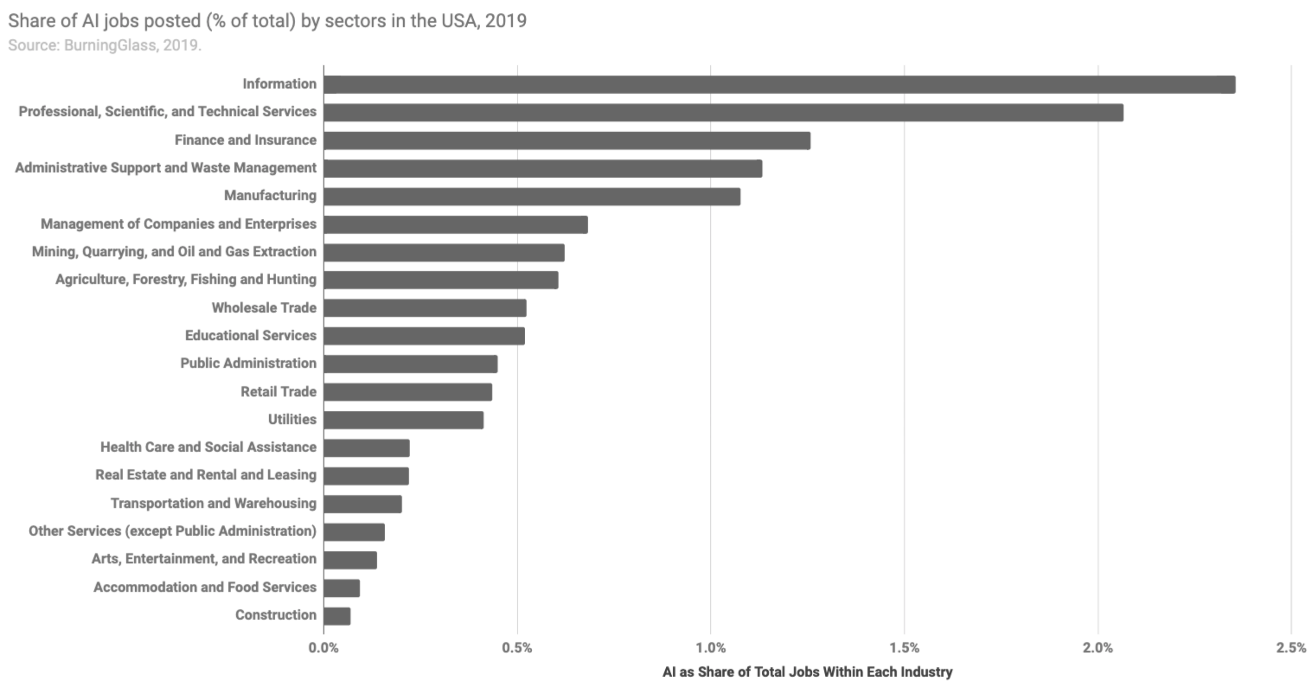



Fig. 4.1.3.

## US Labor Demand By Sector

Share of AI jobs posted (% of total jobs posted) by Industry, 2010-19

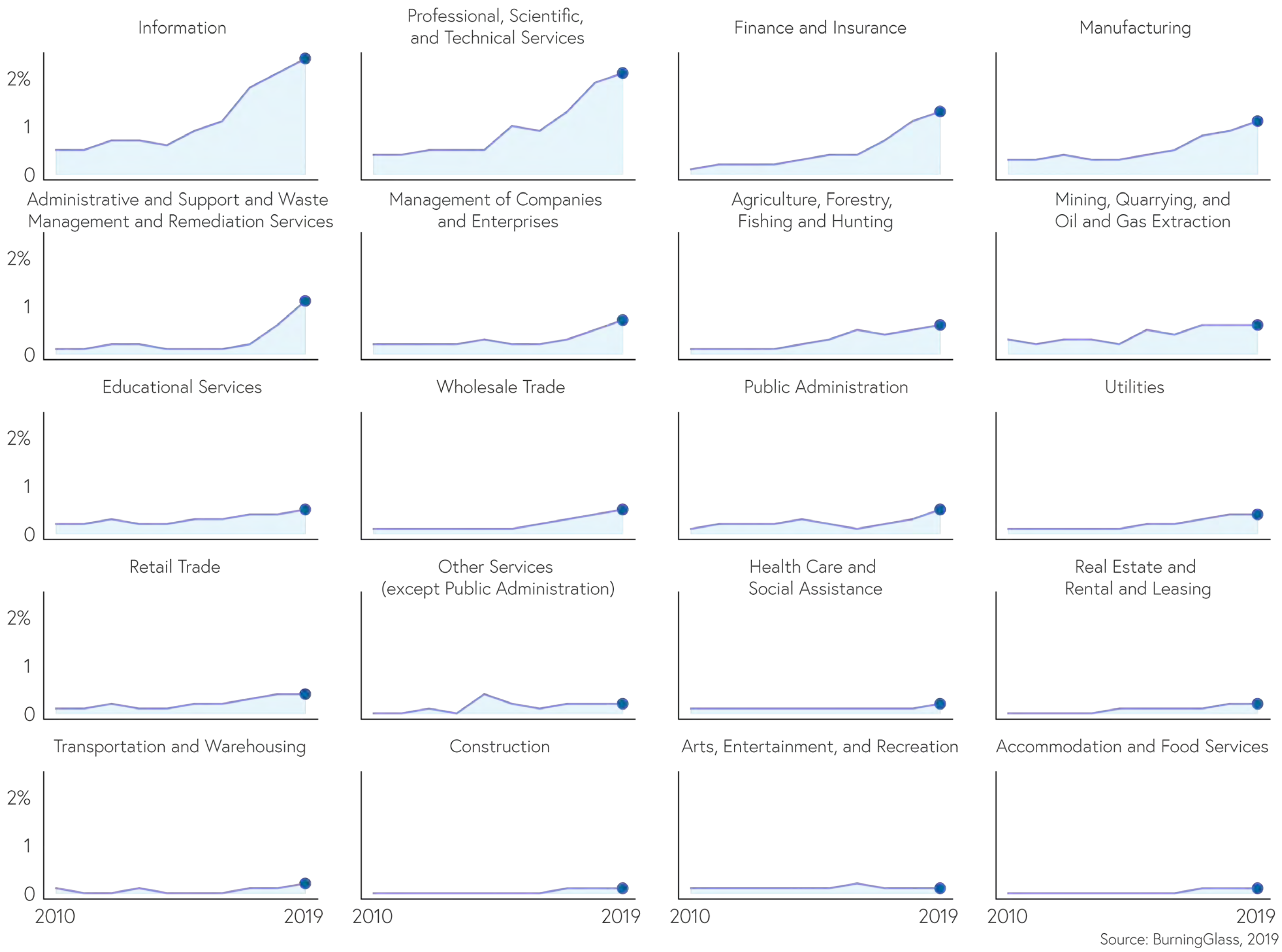



Fig. 4.1.4.

**AI labor demand is growing in significance especially in hi-tech services and the manufacturing sector.**

## Global Skill Penetration

**Penetration and Relative Penetration of AI Skills**

Using LinkedIn data, the **Penetration of AI Skills** in a given country is defined as the average share of AI skills among all the top 50 skills in each occupation, across all occupations in that country. This metric can also be computed at the sector-country level.

Since different countries have different occupation sets, this penetration rate may not be directly comparable across countries. To allow for cross-country comparisons, the **Relative Penetration of AI skills** is defined as the ratio between the penetration of AI skills in a given country and the average penetration of AI skills across all countries in the sample, considering only the overlapping occupations between the country and the sample.

Skills data are drawn from the member profiles of professionals on the LinkedIn platform. Specifically, the data are sourced from the skills listed on a member's profile, the positions that they hold and the locations where they work.

LinkedIn has categorized and standardized the over 35,000 unique skills on its standard platform into a set of skills clusters using nonlinear embedding spaces. These clusters are seeded by humans and subsequently applied to co-occurrences of skills on profiles across the entire platform. Skills are related by distance in "skill space." Closely-related skills are tagged with a common human-curated cluster name. Skills that co-occur less frequently are classified in separate clusters. Neural skills embeddings are supplied by the LinkedIn engineering team.

In order to compute this metric, LinkedIn first calculates a weight for each skill based on the prevalence of that skill in a particular segment, such as a particular geography, sector, and/or occupation, and compares it to other segments of the labor market. First, all members who hold the occupation during the relevant period are included in the analysis. Then a frequency measure is assigned to each skill by calculating the number of times members list the skill under the "skills" section of their LinkedIn profile. Note that skills are only included in the analysis if they were specifically added during the period for which the individual has held that position. The skills that are added by fewer than or equal to 10 members during the pre-defined period are dropped to reduce 'noise' in the skills data.  Skills are only captured if they are relevant to the role and enables a comparison between skills profiles over time. Finally, each occupation-skill pair is weighted following a term frequency–inverse document frequency (TF-IDF) model: skills that are generic and appear in multiple occupations are down-weighted. The result is a list of skills that are most representative of that occupation in that sector and country.

See also: Data Science in the New Economy Report (World Economic Forum, July 2019).

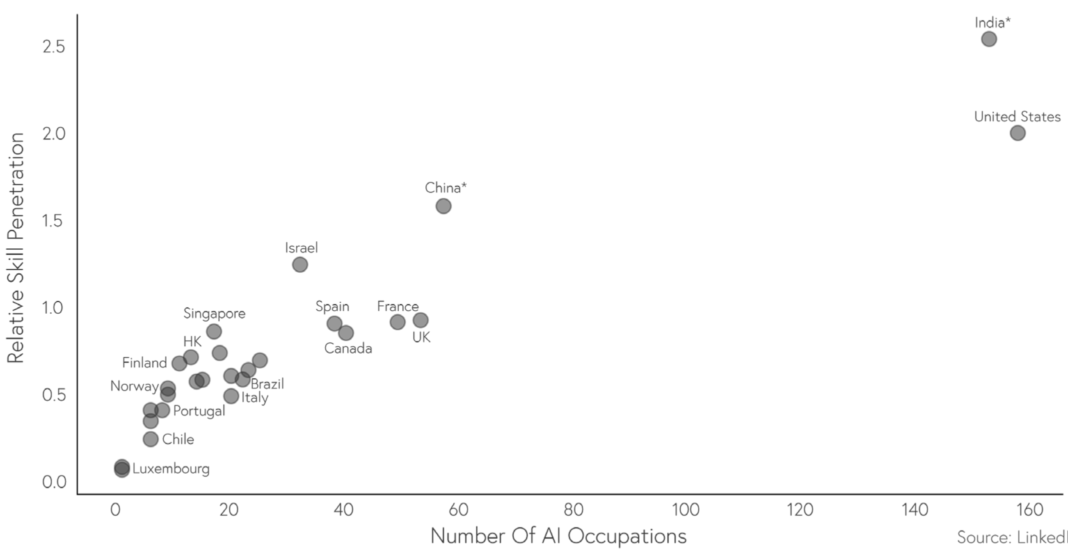
## Skill Penetration

Which countries have the highest penetration of AI skills? The relative skill penetration rate metric is based on a method comparing the share of AI skills for each country against a global average/benchmark based on the same set of occupations. For a given country, the relative skill group penetration is the ratio between the penetration rate of a given skill group in each country and the global average penetration rate.

An interesting example is India. The average penetration of AI skills in India in selected sectors is 2.6 times the global average across the same set of occupations. It is interesting to note that India is expected to add over 10 million new young people to the labor force every year over the next decade ([Economic Times, 2018]). This gain in labor talent raises an interesting question of how India will use its demographic dividend to train, produce, and export sophisticated AI products and services for inclusive growth and development.

The results below are presented for sample countries where there is sufficient coverage (Figure 4.1.5).[9] An occupation on LinkedIn is one of roughly 15,000 job categories added by LinkedIn members; Members have also added 35,000 types of skills to their profiles The horizontal axis of the chart is the number of unique occupations in a country that have any AI skills in their top 50 skills, as reported by LinkedIn members. This is not a per-capita metric. The results represent pooled skill additions between 2015 and 2018. The three step process to calculate relative skill penetration rates are documented in the Appendix. Bar charts in Appendix show the ranking of countries on these measures.

**National Comparison of Skill Penetration and Number of Unique AI Occupations**




Source: LinkedIn, 2019

Notes: *China and India were included in this sample due to their increasing importance in the global economy, but LinkedIn coverage in these countries does not reach the 40% of the workforce. Insights for these countries may not provide as full a picture as other countries, and should be interpreted accordingly. Number of unique AI occupations refers to the number of unique job titles with high skill intensity.

Fig. 4.1.5.

*"While the impact of AI on economies has been primarily concentrated in developed economies on the technological frontier, it's important to note its impact on developing economies. In China and India, the two largest developing economies, we're seeing a similarly large surge in AI skill prevalence."*
Guy Berger, Principal Economist at LinkedIn, 2019

[9] Countries and regions with significant representation of their workforce on LinkedIn (roughly >40%) included in this analysis are United States, Netherlands, Ireland, Denmark, Australia, United Kingdom, Luxembourg, Canada, Singapore, Belgium, New Zealand, Norway, Sweden, United Arab Emirates, France, Portugal, Switzerland, Chile, Spain, Italy, Hong Kong (SAR), Finland, Israel, Costa Rica, Brazil. China and India are included in this sample due to their increasing importance in the global economy, but LinkedIn coverage in these countries does not reach the 40% of the workforce. Insights for these countries may not provide as full a picture as other countries, and should be interpreted accordingly.

## Skill Penetration

In order to provide a deeper sectoral decomposition of AI skill penetration across sectors and countries, the following sample top five sectors with the highest AI skill penetration globally are chosen: Software & IT Services, Hardware and Networking, Education, Finance, and Manufacturing (Figure 4.1.6). India, the US, France, China, and Israel are frequently among the top countries in AI Skill Penetration across all countries. The US ranks in the top 5 countries for AI skill penetration across all sectors. As noted earlier, the large labor pool in India and its IT skills provide hope for cautious optimism as AI could become a driver for occupational diversity, jobs and growth. China only shows up in the top 5 ranking in the education-related skill penetration. Other pockets of specialization worth highlighting include Norway and Israel in AI skills in Software and IT; Norway, France, and Sweden in Hardware and Networking; France, Israel, and Sweden in hardware and networking as well as manufacturing; Spain and Switzerland in education; and the UK and Canada in finance.

### Global AI Skill Genomics: Ranking of Sectoral Relative AI Skill Specialization by Countries, 2018

#### Sectoral Rankings of AI Skill Penetration Scores, by Country

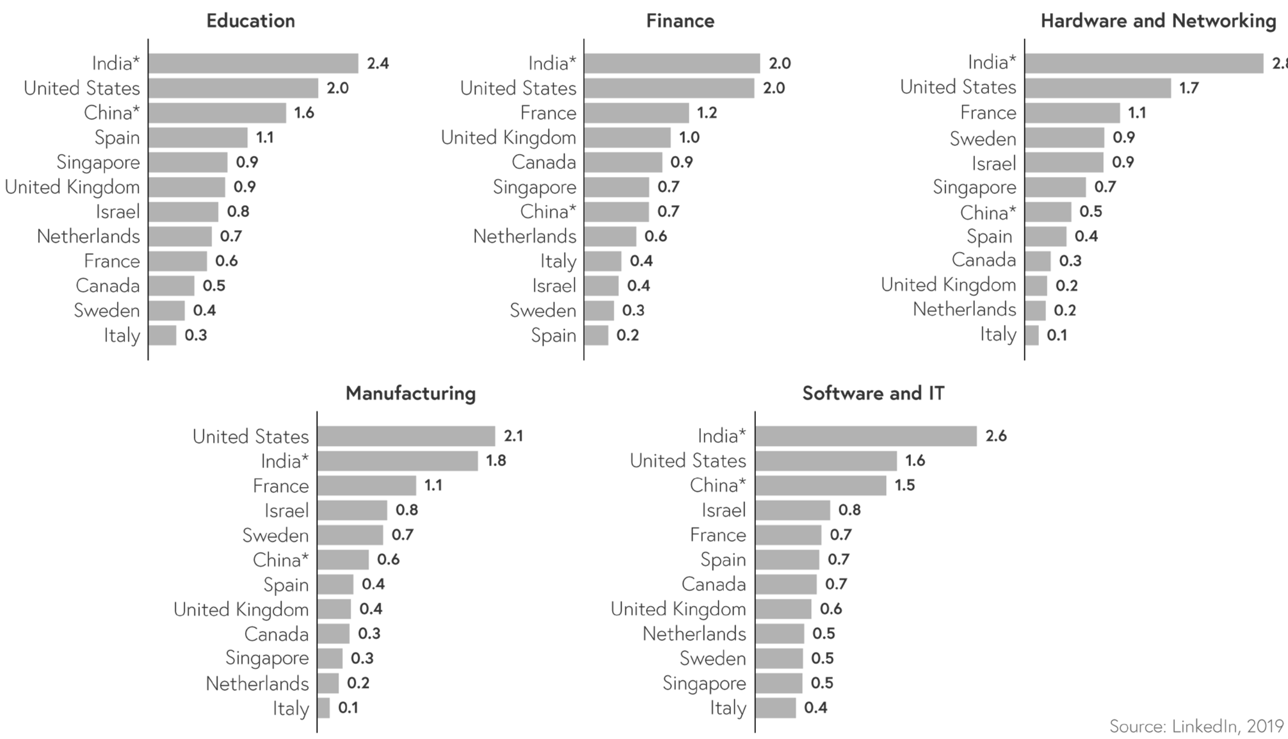



Fig. 4.1.6.

*China and India were included in this sample due to their increasing importance in the global economy, but LinkedIn coverage in these countries does not reach the 40% of the workforce. Insights for these countries may not provide as full a picture as other countries, and should be interpreted accordingly.

**How will India utilize its demographic dividend to train, produce, and export sophisticated AI products and services for inclusive growth and development?**

## Inclusion: Global Skill Penetration By Gender

Which countries exhibit relatively higher AI skill intensity by gender? The chart below presents the ranking of countries based on AI skill penetration for female and male labor pools (Figure 4.1.7).[10] Two trends are worth noting. First, men tend to report AI skills across more occupations than women in all countries in the sample. Second, while countries with high AI skill penetration for men are more likely to exhibit high AI skill penetration for women as well, this pattern is not universal. Some European countries --including the Netherlands, Switzerland, and France--rank significantly higher when considering only women than when considering men. More granularly, the results indicate that the average occupation held by women in India exhibits over 2.6 times the global average AI skill penetration, while the average occupation held by men in India is 2.7 times the global average AI skill penetration. In terms of AI skill reported for women, India is followed by the US (1.5), Netherlands (1), Switzerland (0.94), and France (0.90). For example, India has 55 occupations where women report AI skills whereas men report AI skills in 127 occupations in 2015-2018.

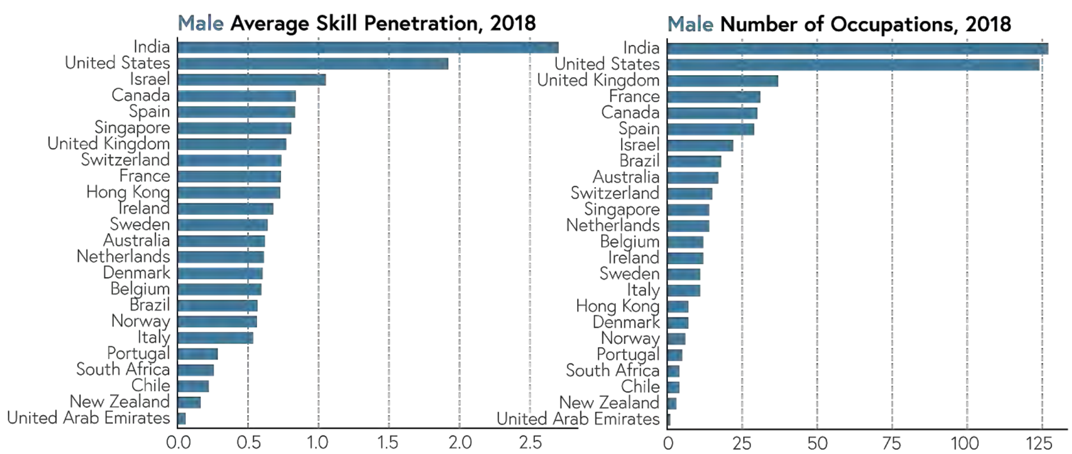
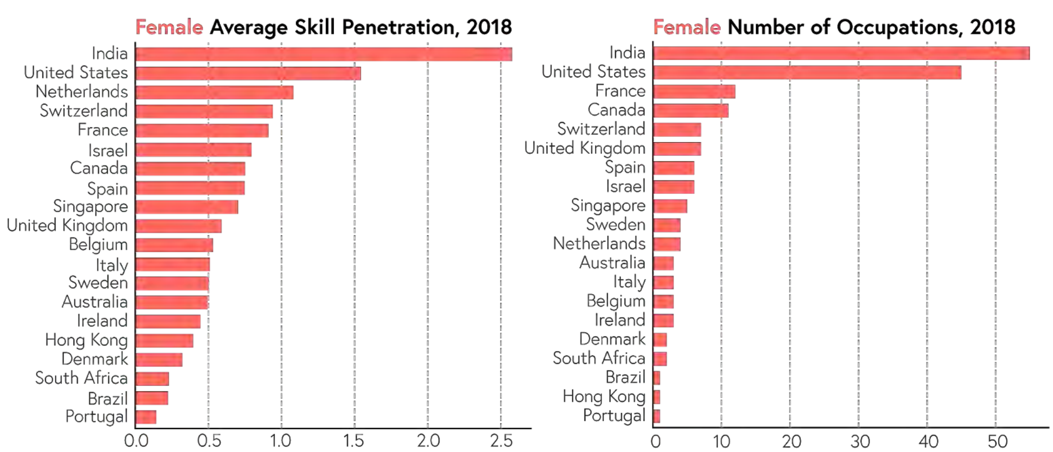



Fig. 4.1.7a.

Source: LinkedIn, 2019

* India was included in this sample due to its increasing importance in the global economy, but LinkedIn coverage does not reach the 40% of the workforce. Insights for this country may not provide as full a picture as other countries, and should be interpreted accordingly. Number of unique AI occupations refers to the number of unique job titles with significant skill intensity.




* India was included in this sample due to its increasing importance in the global economy, but LinkedIn coverage does not reach the 40% of the workforce. Insights for this country may not provide as full a picture as other countries, and should be interpreted accordingly. Number of unique AI occupations refers to the number of unique job titles with significant skill intensity.

Source: LinkedIn, 2019

Fig. 4.1.7b.

*"Like a lot of other promising -- but not quite mature -- technologies, the AI talent pool is growing at an extremely fast pace. And the pace at which these folks are being hired is growing even faster. More than ever before, this surfaces the need for public and private sector interventions that ensure enough workers are trained and reskilled to meet the rapidly-growing demand for AI skills."*
*Guy Berger, Principal Economist at LinkedIn, 2019.*

[10] "Female" and "male," "women" and "men" are the terms used in the data set. Samples in this analysis consider an additional data filter: having gender data on at least 66% of LinkedIn members. Note that China does not meet this threshold and is thus excluded.

## Labor demand and skill penetration by US state

Here the regional AI labor demand and skill penetration by states in the US is examined, followed by metropolitan areas, and cities.

The first chart plots the (relative) importance of AI labor demand as the AI share of total jobs posted on the y-axis and the (absolute) size of labor demand measured as the natural log of total number of AI jobs posted between 2018 and September, 2019 (Figure 4.1.8). Appendix graphs present the ranking of the absolute and relative AI labor demand metrics for US states.

The results show that Washington state has the highest relative AI labor demand with almost 1.4% of total jobs posted are AI jobs. Washington is followed by California with 1.3%, Massachusetts with 1.3%, New York with 1.2%, and the District of Columbia (DC) with1.1%, and Virginia with 1 AI jobs. There are 5 states in addition to Washington, DC where over 1% of total jobs posted are AI jobs. Majority of states lie between 0.2 and 1% of total jobs posted.

In absolute terms California has the largest number of AI jobs posted. Over 93,000 AI jobs were posted in California since 2018. This is three times the volume of the next state, New York, with 30,000 AI jobs posted in AI. Texas was next with over 24,000 jobs posted, followed by Massachusetts with over 19,000, Washington over 18,000, and Virginia over 15,000. The full state level AI labor demand metrics are available here.

**Relative importance of AI jobs and absolute size of AI labor demand, 2018-19**

Source: Burning Glass, 2019.

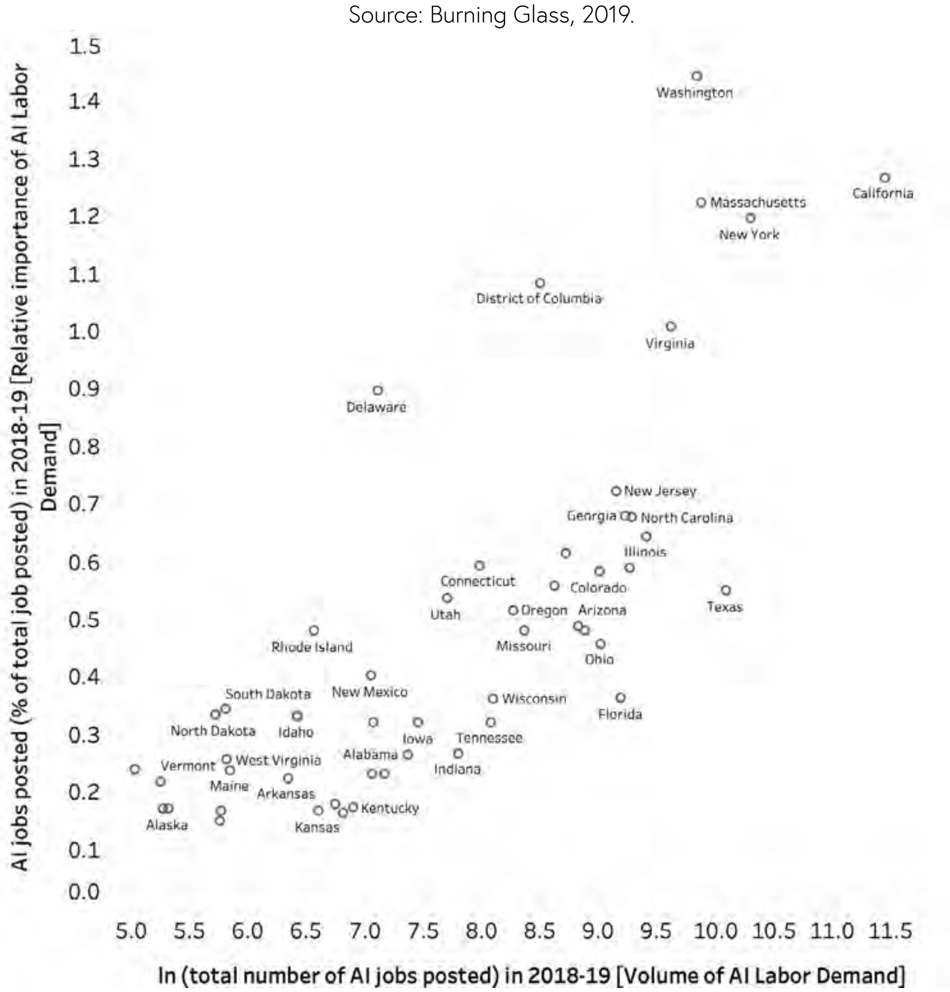



Fig. 4.1.8.
Note: The chart plots the sum of AI job postings in 2018 which includes data up until September of 2019.

## Regional Dynamics (US)

Has US AI-related labor demand converged across states over the last decade? The answer is mixed. In terms of absolute labor market demand for AI jobs, the evidence points towards unconditional convergence i.e. the states that had low labor market demand 10 years ago in 2010 witnessed relatively faster growth in AI job postings than big states. Appendix charts show unconditional convergence in absolute labor demand. However, the evidence also points towards unconditional divergence in relative AI labor market demand. Appendix chart on unconditional divergence in relative US state level AI labor demand shows that the relative importance (or the relative size of AI job postings) has grown fastest in initially large AI states. For example, states like Washington, California, Massachusetts, Virginia, New York, Maryland or DC witnessed an increase in AI share of total employment greater than 0.2 percentage points since 2010.

US state maps show the average annual growth in AI jobs between 2010-19 (Figure 4.1.9a) and AI relative skill penetration respectively (Figure 4.1.9b). With convergence in absolute AI job posting growth, initial conditions matter. States like Wyoming starting with a very small base experience faster growth in AI job postings of over 70%, followed by North Dakota with over 65%, Nevada with over 50%, Rhode Island and Montana with over 45% average annual growth between 2010-10. However, in terms of AI skill penetration only states such as California, New York, and Texas appear to have higher relative AI skill penetration.

**Average annual growth in AI jobs postings for US States, 2010-19**

Source: Burning Glass, 2019.

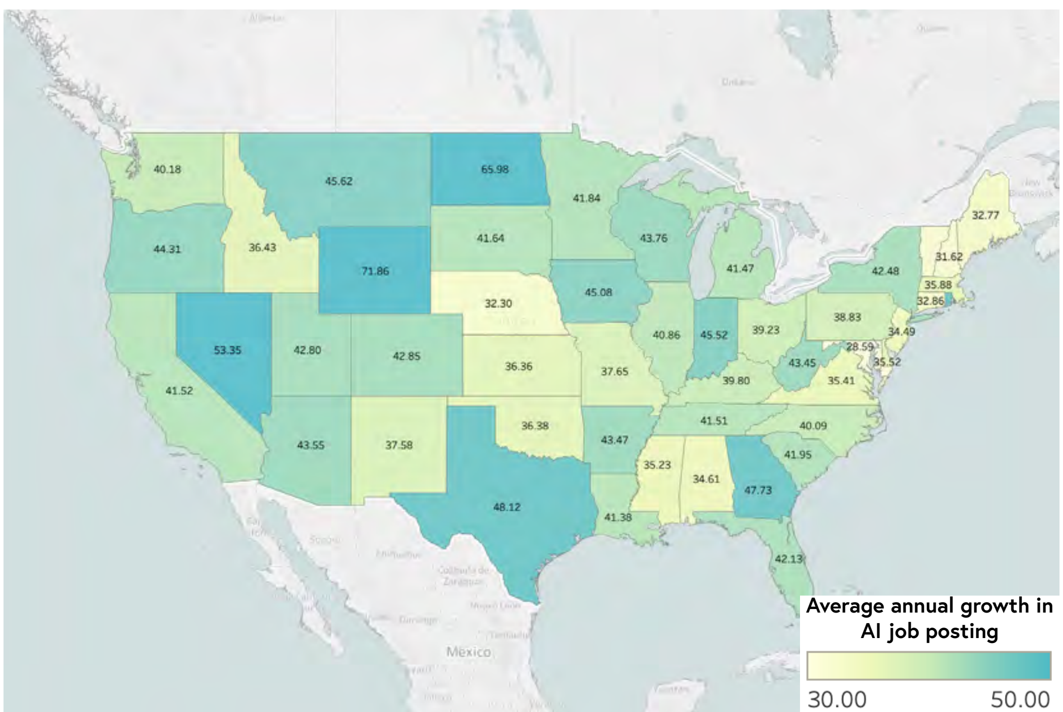



Figure 4.1.9a

Note: The color represents the average annual growth in AI job postings as measured by the natural log difference between the sum of AI jobs posted between 2018 and September, 2019 - the natural log of total AI jobs posted between 2010-13, divided by the time-period difference.

**The states that had low labor market demand 10 years ago in 2010 also witnessed fast growth in AI job postings along the big states.**

## Regional Dynamics (US)

**US States AI Skill Penetration, 2018**

Source: LinkedIn Economic Graph, 2019.

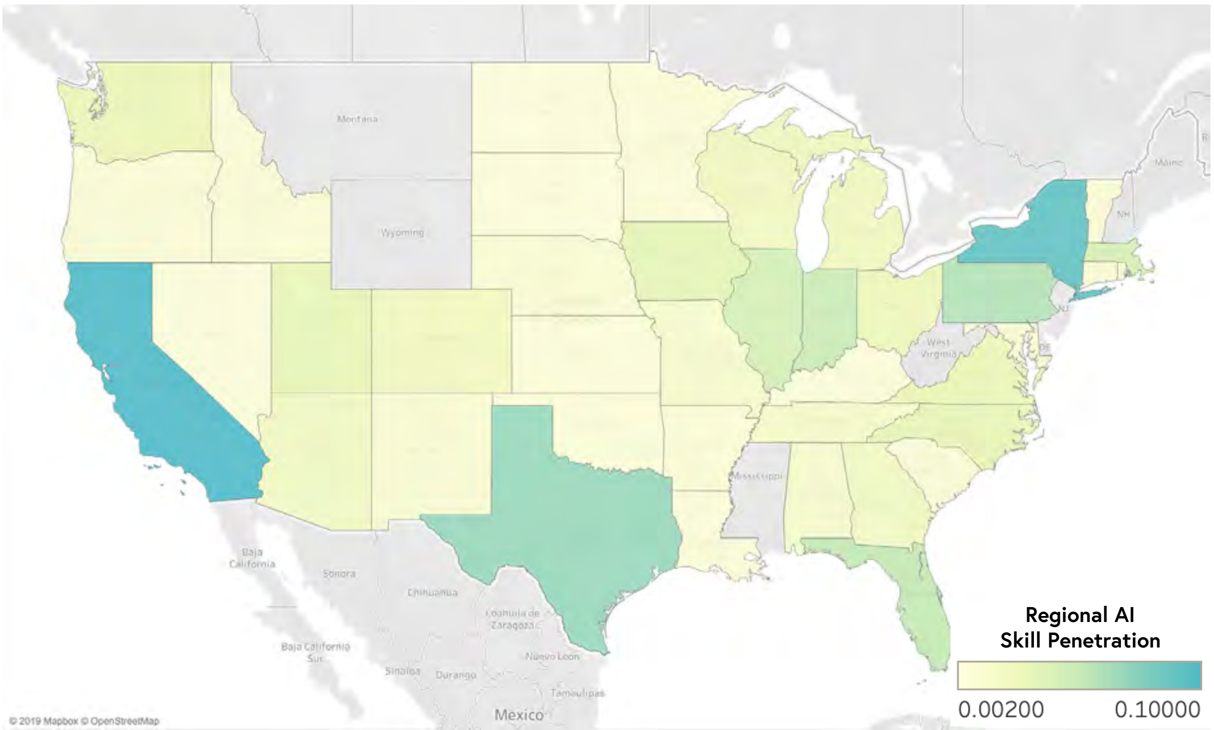



Fig. 4.1.9b.

## Labor Demand and Skill Penetration by US Metropolitan Areas and Cities

What are the deeper regional dynamics of AI job demand in the US? Is demand primarily concentrated in tech epicenters, or is it dispersing across the country? The map of the US for Metropolitan Statistical Areas (MSA's) is presented below (Figure 4.1.10). The size of the bubble represents the absolute size of labor demand, i.e., total number of AI jobs posted. The largest bubble size represents the total number of AI jobs posted 20,000 jobs in a given MSA. The color schematic represents the relative importance of AI labor demand, with the shade of blue representing any MSAs with greater than 1 percent share of AI jobs in total AI jobs posted. Readers should note that the sample size of smaller MSAs is not reliable for a small sector like AI; hence the data is missing.

In addition to details on the data and methodology, readers can also observe the evolution of AI jobs and the economic impact across different regions. The methodology is discussed in Appendix.

**Regional Dynamics of AI labor demand in the US**

Source: Burning Glass, 2019

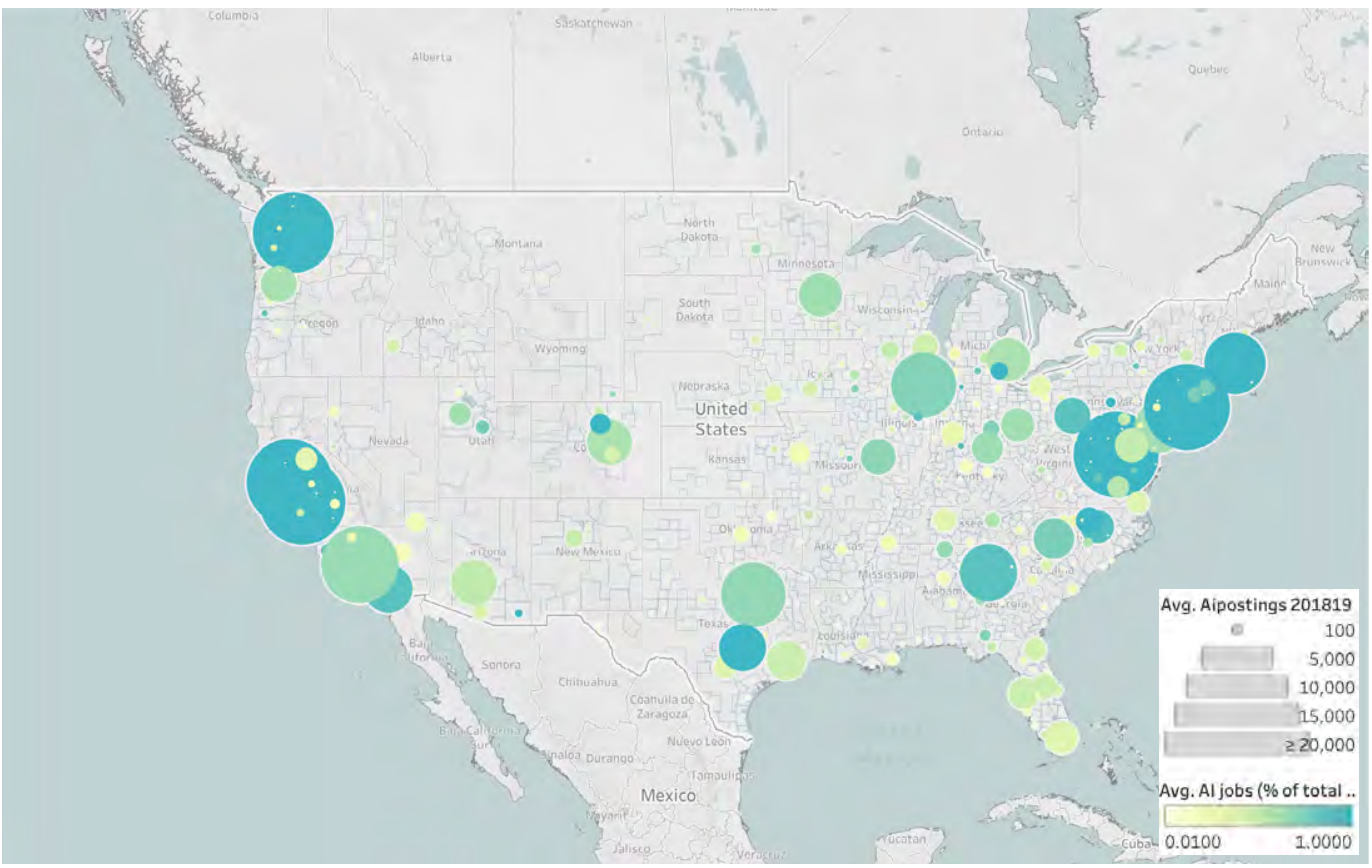



Fig. 4.1.10.
Notes: Alaska and Hawaii have not been presented for presentational brevity.

## Labor Demand and Skill Penetration by US Metropolitan Areas and Cities

Is there a convergence in AI job posting across metropolitan areas across the US? The chart below plots the average annual growth in total number of AI jobs as a share of IT jobs between 2010 and 2019 for almost 400 MSAs on the vertical axis and the natural log of total number of AI jobs posted in 2010 on the horizontal axis (Figure 4.1.11). The results are again mixed but with no convergence across MSAs for total number of AI jobs posted and unconditional divergence in relative AI labor demand. The detailed graphs are presented in Appendix. In the chart below, the graph is broken into four quadrants. The top right quadrant represents the areas that already had high AI job demand and also witnessed rapid growth over the last decade. The top left quadrant represents the areas that are emerging hubs of AI job demand. The bottom left quadrant had a relatively low stock of AI jobs ten years ago and further shrinking since then, while the bottom right quadrant had a relatively high stock of AI jobs in the past but shrinking AI demand since then.

In absolute terms many emerging areas have high growth in AI labor demand. Columbus, Ohio; Knoxville, Tennessee; Jacksonville and Gainesville, Florida; Beckley, West Virginia witnessed the fastest absolute growth in AI job posting starting from a very small base. Knoxville has not been widely discussed. roximity to Oak Ridge National Lab (ORNL) may have influenced its growth. ORNL and Department of Energy (DOE) are significantly ramping up their AI activities and adding to their workforce in this field. This growth could also contribute to local businesses who might work with ORNL, or work in related areas. Since ORNL is a major employer in a relatively small metropolitan area, their ramp-up in AI would be statistically significant to the workforce opportunities in the area. As a side note, anecdotally, in the past it has been mentioned that Oak Ridge has one of the highest concentrations of PhDs in the country, again because the town is small and ORNL is large. The other emerging areas of AI job demand include Asheville, North Carolina; Pittsburg, Pennsylvania; Ann Arbor, Michigan; Fargo, North Dakota; Virginia Beach-Norfolk, Virginia and North Carolina. Ranking of top MSA with high absolute and relative growth in AI labor demand and top MSA with shrinking AI labor demand are presented in the Appendix graphs.

**No clear convergence: Many small metropolitan with low initial stock of AI jobs also experienced fast growth in AI labor demand (2010-19)**

Source: Burning Glass, 2019

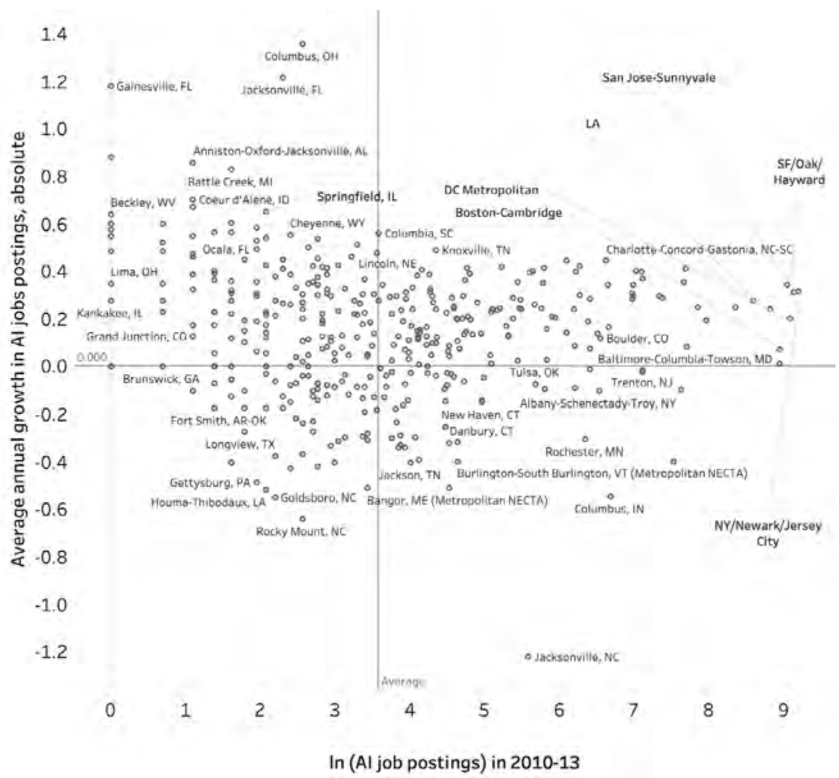



Fig. 4.1.11.

*"The growth of AI labor demand in smaller cities and regions of the US illustrates the tremendous potential of AI to generate new types of work across our Nation. Policy strategies for AI education and workforce training – including the President's American AI Initiative and the National Council for the American Worker – will ensure that America's workers are capable of taking full advantage of the opportunities of AI."*
Lynne Parker, Deputy US Chief Technology Officer

## Labor Demand and Skill Penetration by US Metropolitan Areas and Cities

Table 4.1.1 shows the ranking of AI skill penetration for US regions based on LinkedIn data. Bryan College Station in Texas has the highest relative AI skill penetration in the country, followed by San Francisco Bay Area, Lafayette, Indiana, Binghamton, New York, and Urbana-Champaign, Illinois. This evidence points to greater occupational skill diversity in emerging hubs in addition to Silicon Valley and New York City. Appendix table provide detailed ranking for major US cities on AI skill penetration and provides related results based on LinkedIn data that show unconditional divergence in AI skills across the US regions indicating that the growth in AI skill penetration is faster in areas that initially had high skill penetration. However, the time sample is limited to three years.

**Ranking of AI Skill Penetration for US Cities, 2018**
Source: LinkedIn, 2019.

| City | Rank | City | Rank |
|---|---|---|---|
| Bryan-College Station, TX | **1** | Santa Barbara, CA | **14** |
| San Francisco Bay Area, CA | **2** | Springfield, MA | **15** |
| Lafayette, IN | **3** | Madison, WI | **16** |
| Binghamton, NY | **4** | Raleigh-Durham, NC | **17** |
| Urbana-Champaign, IL | **5** | State College, PA | **18** |
| Pittsburgh, PA | **6** | Austin, TX | **19** |
| Gainesville, FL | **7** | Provo, UT | **20** |
| Seattle, WA | **8** | | |
| Rochester, NY | **9** | | |
| San Diego, CA | **10** | | |
| Boston, MA | **11** | | |
| Des Moines, IA | **12** | | |
| Bloomington, IN | **13** | | |

Table 4.1.1.

*"Historically, technology can be a vehicle for rising inequality. Policy and social interventions can either mitigate or worsen those trends, so having access to comprehensive data on AI jobs, skills, and tends is critical. These insights help us avoid the bad interventions, and instead invest in those that equitably share the enormous gains that the next wave of technological innovations could generate."*
Guy Berger, Principal Economist at LinkedIn, 2019

## Measurement Questions

- Traditional statistics and labor force surveys do not yet include AI and related occupations. Thus, online jobs platforms function as proxy indicators to assess the evolution and growth in AI labor market indicators, and largely demonstrate the demand side of labor market outcomes. How can more direct data about the AI workforce be gathered?

- In regard to the data and methodology, one main area for organization is a standard topology of AI skills and keywords to measure AI job metrics. At the moment different online jobs platforms use different processes for data and may have self-selection bias in different country or regional context. Could platforms define standard ways of tagging AI jobs to facilitate further study?

- Data on AI jobs across countries and within countries is not consistently available. More and better collection of data will be required to consistently track developments.

## Global

Globally, investment in AI startups continues its steady ascent. From a total of $1.3B raised in 2010 to over $40.4B in 2018 alone (with $37.4B in 2019 as of November 4th), funding has increased with an average annual growth rate of over 48% between 2010 and 2018 (Figure 4.2.1a). We consider only AI companies that received more than $400k in investment. The number of AI companies receiving funding is also increasing, with over 3000 AI companies receiving funding in 2018 (Figure 4.2.1b). Between 2014 and 2019 (through November 4th), a total of 15,798 investments (over $400K) have been made in AI startups globally, with an average investment size of approximately $8.6M.

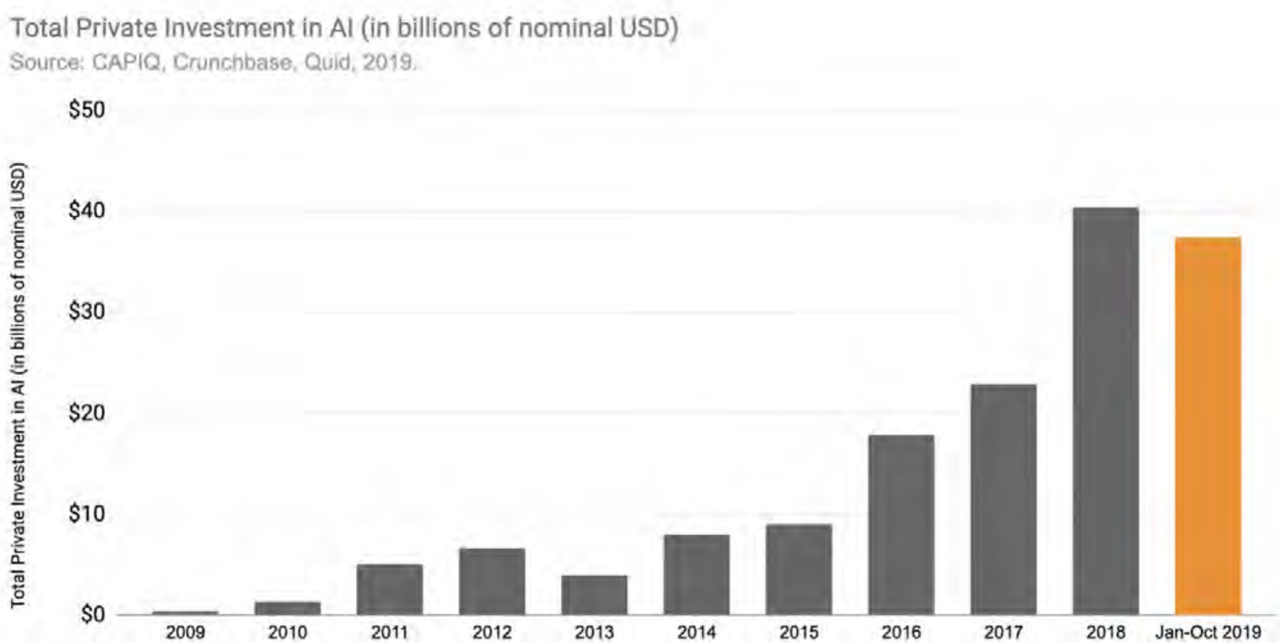



Fig. 4.2.1a.

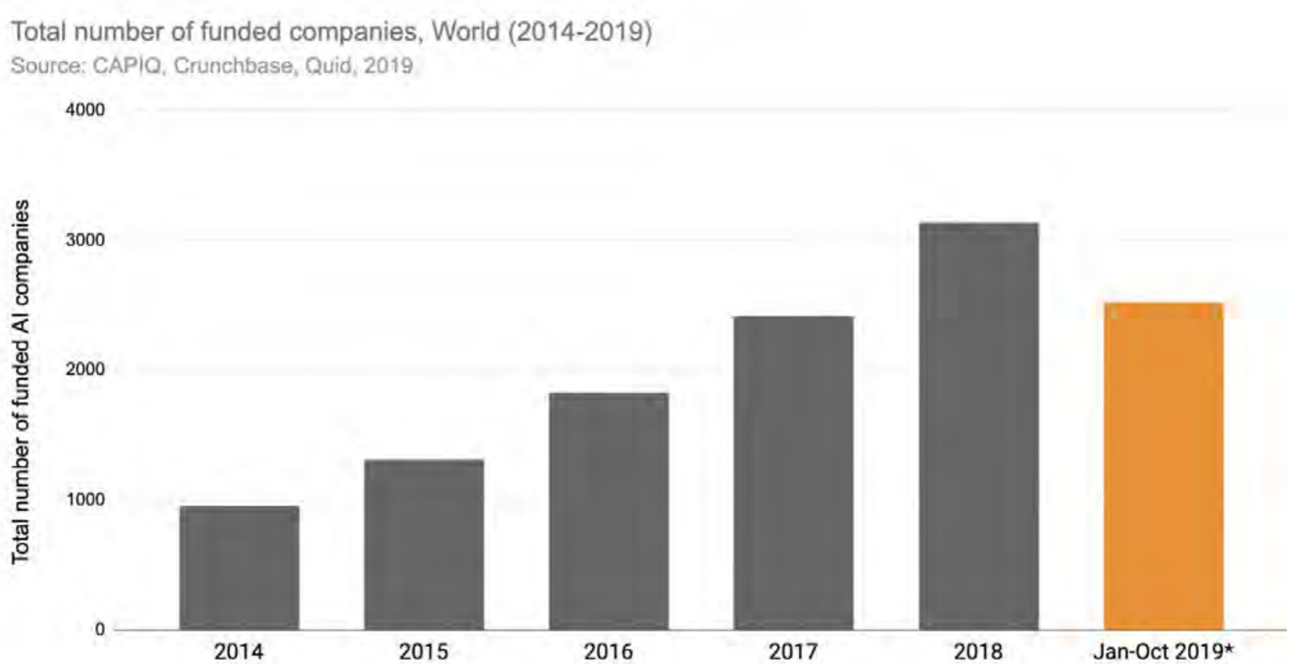



Fig. 4.2.1b.

## Country

The United States remains dominant when it comes to the number of funded startups and, in general, has been a consistent leader in AI funding. However, a select few Chinese firms received exceptionally high levels of investment in 2018, which pushed the country closer to parity with the United States (Figure 4.2.2). The underlying detailed time series data can be found here with Appendix graphs providing more detailed country-specific charts.

Which countries appear to be emerging as AI hubs normalized for the size of the country? When adjusted for per capita terms (to reflect the number of startups or investment relative to a country's size), it's actually Israel that has invested the most over the last year, followed by Singapore and Iceland (Figure 4.2.3). During that period, Israel and Singapore also had the largest number of funded startups, trailed a ways back by Iceland, Switzerland, and Canada.

The two graphs above provide data for select economies, however, the full list of countries is available in the appendix. You can also access underlying time series data or appendix graphs that provide more detail with country-specific charts.

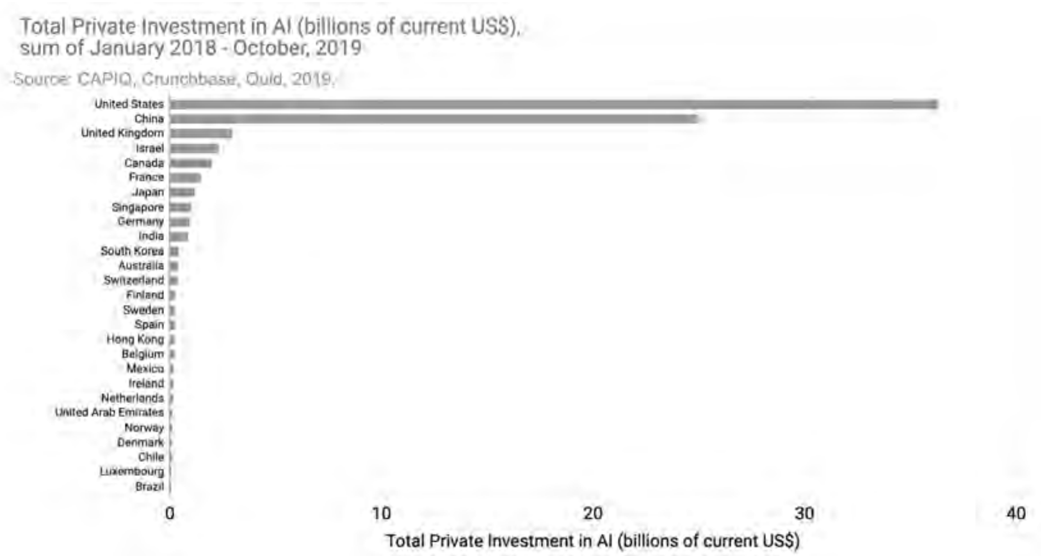



Fig. 4.2.2.

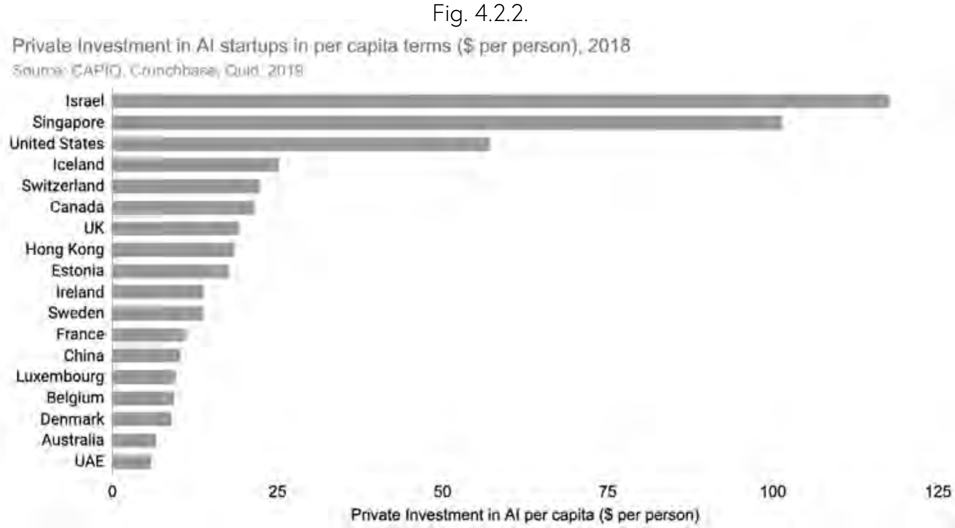



Fig. 4.2.3.

Note: Island economies such as Cayman Islands, British Virgin Islands, Gibralter have been excluded from the sample.

**US, Europe, and China take the lion's share of global AI private investment, while Israel, Singapore, and Iceland invest substantially in per capita terms.**

## Sector

Which are the largest and fastest growing sectors for AI-related investment? Seen in the first graph below (Figure 4.2.4), Autonomous Vehicles (AVs) received the lion's share of global investment over the last year with $7.7B (9.9% of the total), followed by Drug, Cancer and Therapy ($4.7B, more than 6.1%), Facial Recognition ($4.7B, 6.0%), Video Content ($3.6B, 4.5%), and Fraud Detection and Finance ($3.1B, 3.9%).

Which sectors are growing the fastest globally? Seen in the graph below (Figure 4.2.5), robot process automation grew most rapidly (over $1B in 2018), followed by supply chain management (over $500M in 2018), and industrial automation (over $500M in 2018). Other sectors like semiconductor chips, facial recognition, real estate, quantum computing, crypto and trading operations have also experienced substantial growth in terms of global private investment.

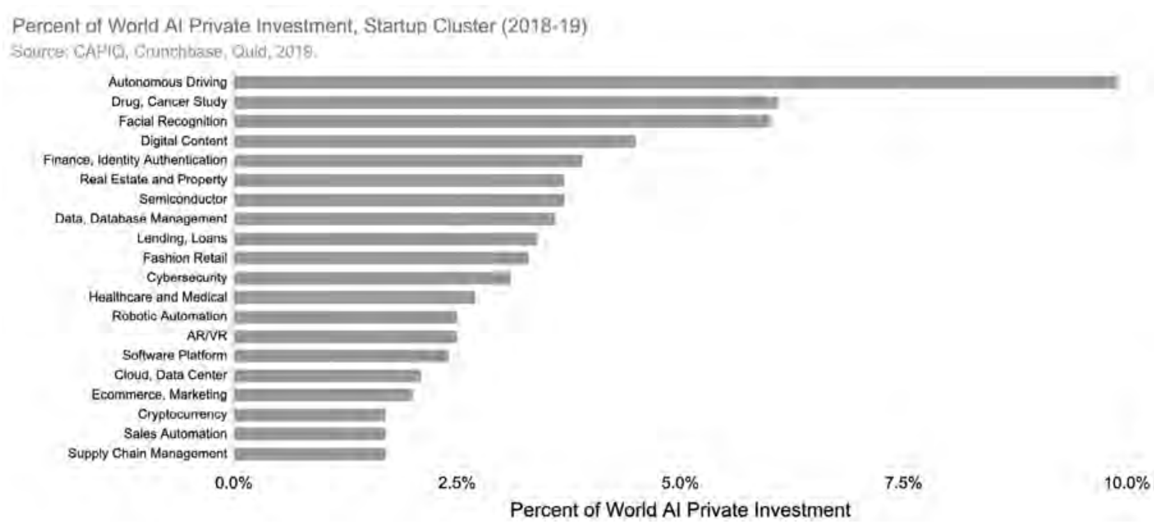



Fig. 4.2.4.
Note: The chart shows the sum of total private AI investments between January, 2018 - October, 2019.

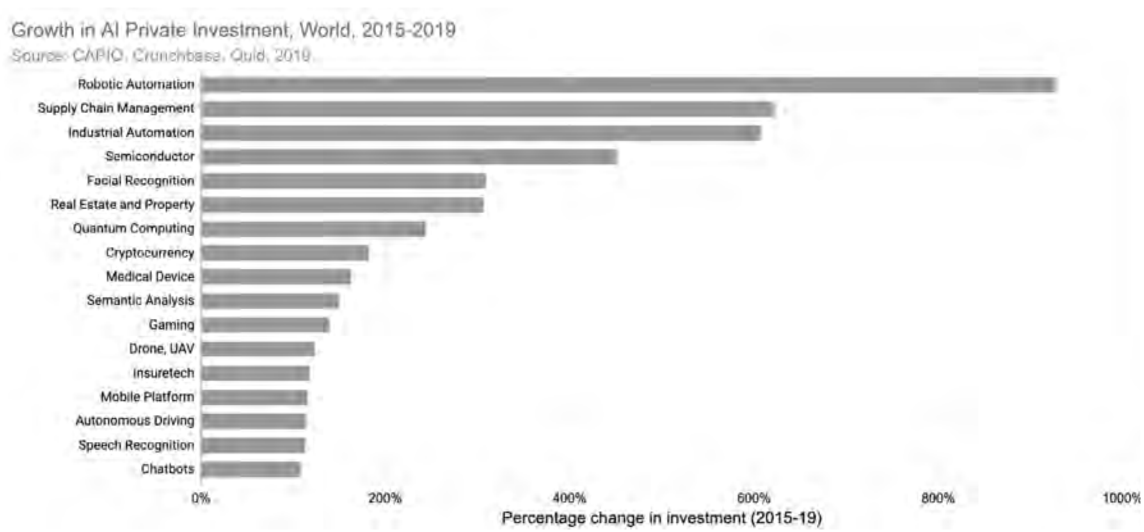



Fig. 4.2.5.
Note: The growth shows growth rate between the 2015-18 (sum) and 2018-19 (sum).

[Investment_Activity_Technical_Appendix]
[Access_Data]

## Focus Areas: Global

Given its diverse range of applications—real estate, gaming, finance, healthcare, and security, just to name a few—AI appears to be transforming into a general purpose technology (GPT). Adoption of AI technologies is widely believed to drive innovation across sectors and could generate major social welfare and productivity benefits for countries around the world. One thing is certain: whether directly or indirectly, AI systems play a key role across businesses and shape the global economy for the foreseeable future. New products and processes are developing across a range of industries: supply chains, robotic process automation, speech recognition, sales automation, accounting, natural security, and many more. Using Quid, 36 different global sectors were identified that are currently utilizing AI technologies.

Globally, 4,403 AI-related companies were identified that received investment during the last year. From 36 distinct sectors, top focus areas included **Data Tools** (5.5% of all companies); **Fashion and Retail Tech** (4.7%); **Industrial Automation, Oil & Gas** (4.3%); **Financial Tech** (4.2%); and **Text Analytics** (4.2%). During that time period, these funded startups received a total of $55.7B in private investment, or roughly $12.6M per startup.

**Global AI startups that have received funding within the last year (July 2018-July 2019)**
Source: CAPIQ, Crunchbase, Quid, 2019.

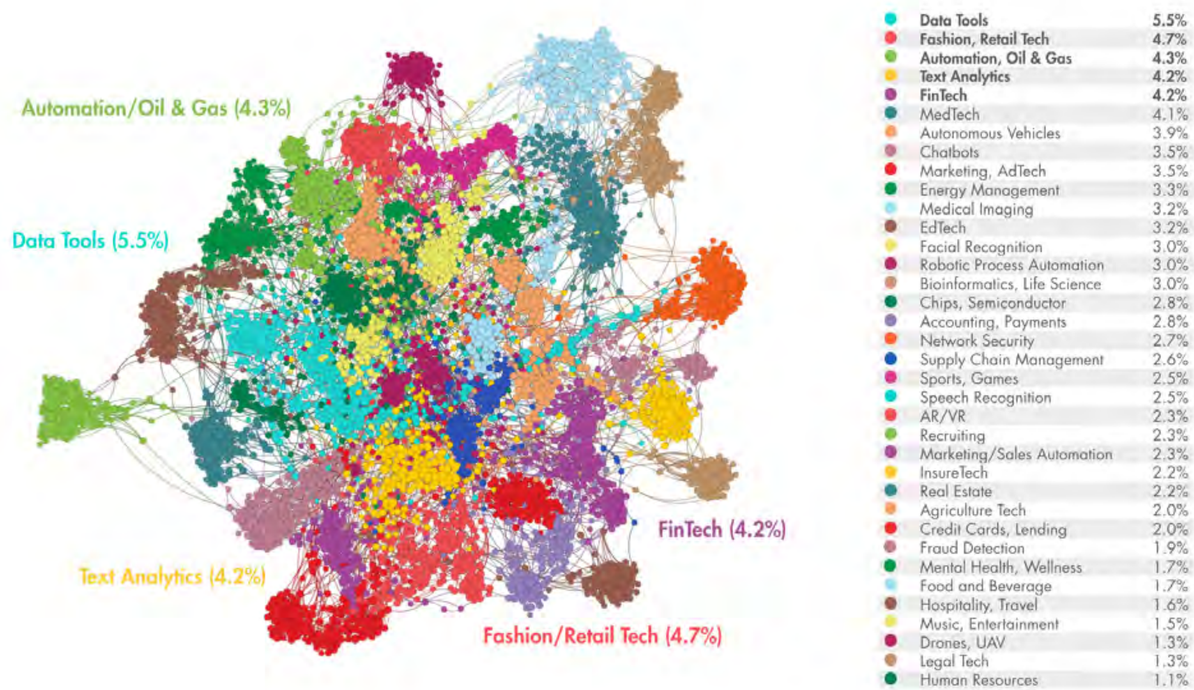



Fig. 4.2.6a.
*Network showing 4,403 global AI startups that received investment between July 2018 and July 2019. Colored by sector with top five highlighted.*

Appendix: How to Red a Quid Network

**AI appears to be transforming into a general purpose technology (GPT). Adoption of AI technologies is widely believed to drive innovation across sectors and could generate major social welfare and productivity benefits for countries around the world.**

## Focus Areas: Regional

How do key focus areas differ across countries and regions? The following graphs overlap specific country or regional data on the global network map to highlight key differences in the volume and variation of startups for the United States, European Union, China, and India. Seen below, the United States and Europe have the most diverse range of startups—each with some representation across all 36 sectors—even though the US has roughly 70% more companies by volume. In the United States, 1,749 startups were identified that received funding across 36 sectors, with top focus areas including: **Data Tools** (8.1% of all companies); **Medical Tech** (5.3%); **Fashion and Retail Tech** (4.7%); **Text Analytics** (4.7%), and **Chatbots** (3.9%). Most of these categories tracked with global trends; even MedTech and Chatbots ranked highly with the #6 and #8 spots worldwide.

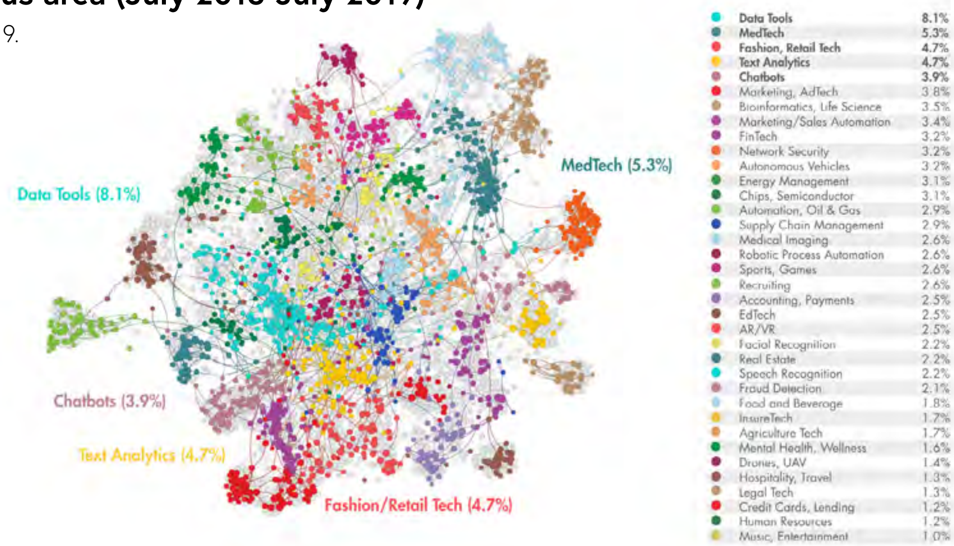
Over the last year, these funded startups received $19.8B of investment, or an average of $11.3M per startup—slightly lower than the global average.
As with the US, each of the 36 global AI sectors has representation in Europe—just on a smaller scale. 993 startups that received funding in the 29 European states were identified during the last year. **Fashion and Retail Tech** (5.7% of all companies) held the top spot, followed by **Medical Tech** (4.4%), **Text Analytics** (4.4%), and a few newcomers to the list: **Marketing and Advertising Tech** (4.3%) and **Autonomous Vehicles** (4%).

During this one year period, funded startups in Europe received a smaller share of the investment pie: a total of $4.6B with an average of $4.7M per startup.

### AI startups in the United States: Companies that have received any funding within the last year, by focus area (July 2018-July 2019)

Source: CAPIQ, Crunchbase, Quid, 2019.

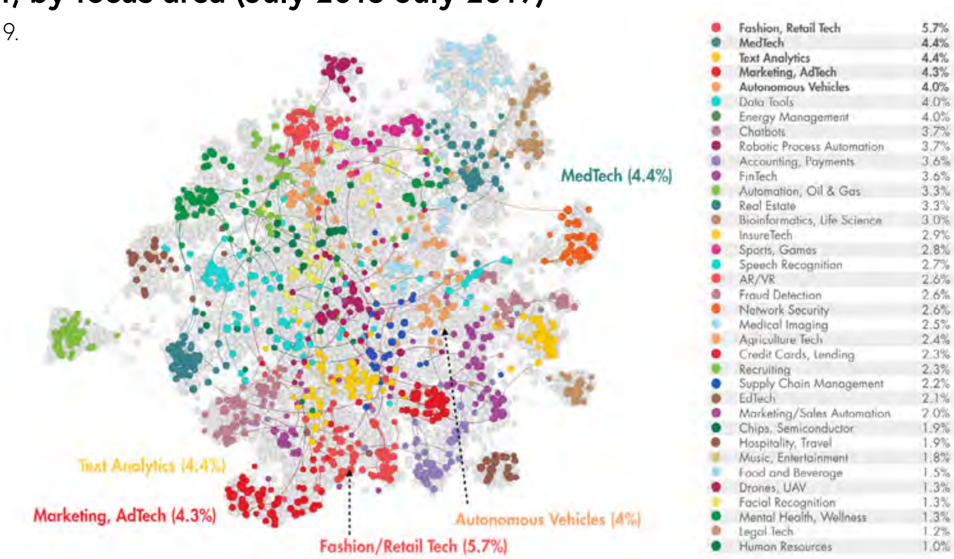
Fig. 4.2.6a.
Notes: Network highlighting 1,749 AI startups in the United States that received investment between July 2018 and July 2019. Colored by focus area with top five labeled.




### AI startups in the European Union: Companies that have received any funding within the last year, by focus area (July 2018-July 2019)

Source: CAPIQ, Crunchbase, Quid, 2019.

Fig. 4.2.6b.
Notes: Network highlighting 993 AI startups in Europe that received investment between July 2018 and July 2019. Colored by focus area with top five labeled.



## Focus Areas: Regional

AI startups in China received much higher rates of investment during this time period than their Western counterparts. The country's 486 funded startups received a whopping $16.6B in investment, or $34.1M per startup (201% more than startups in the US, and 296% more than the global average).

Though fewer in number, Chinese startups had representation across 35 of the 36 identified global AI sectors. Unlike other countries, **Automation/Oil & Gas** (12%) captured the focus of AI activity, followed by **Facial Recognition** (8.8%); **Education Tech** (8%); **Autonomous Vehicles** (6.4%); and **Mental Health/Wellness** (5%).

India lagged far behind the US, EU, and China when it comes to startup founding and investment. Only 139 startups received funding over the last year, with key focus areas including: **Robotic Process Automation** (6.3%); **Credit Cards/Lending** (5.6%); **Chatbots** (4.9%); **Education Tech** (4.9%); and **Hospitality/Travel** (4.9%). Though sparse, Indian startups were quite diverse in number, matching China and just short of the US and EU with 35 out of 36 focus areas represented.

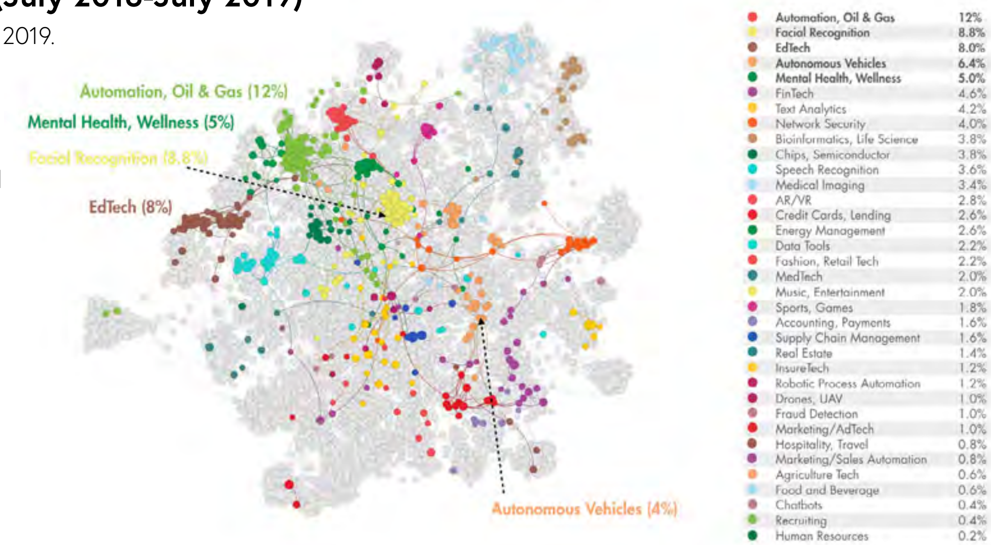
These startups received $360.1M in private investment, or an average of $2.6M per startup—much lower than the US, Europe, or China.

.

### AI startups in China: Companies that have received any funding within the last year, by focus area (July 2018-July 2019)

Source: CAPIQ, Crunchbase, Quid, 2019.

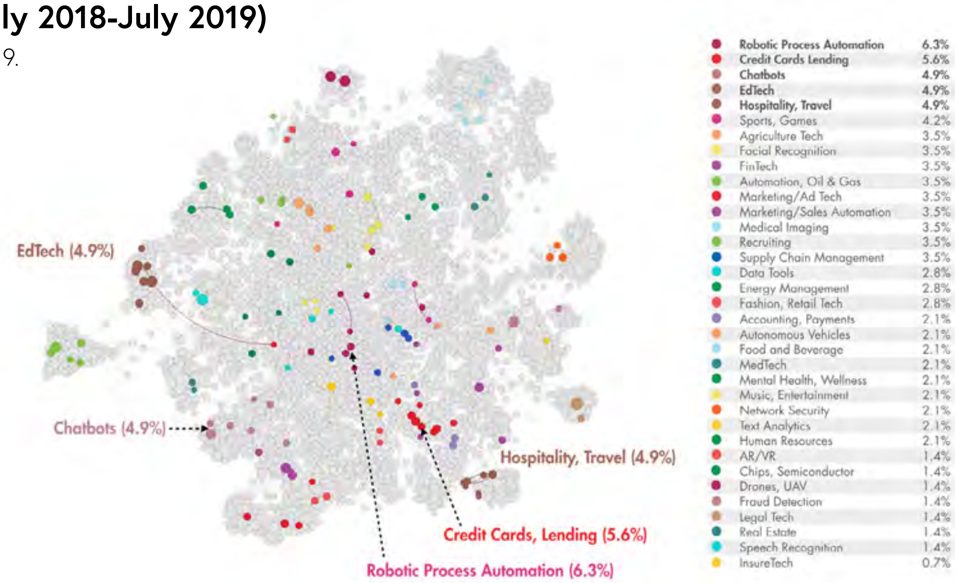
Fig. 4.2.6c.
Notes: Network highlighting 486 AI startups in China that received investment between July 2018 and July 2019. Colored by focus area with top five labeled.




### AI startups in India: Companies that have received any funding within the last year, by focus area (July 2018-July 2019)

Source: CAPIQ, Crunchbase, Quid, 2019.

Fig. 4.2.6d.
Notes: Network highlighting 143 AI startups in India that received investment between July 2018 and July 2019. Colored by focus area with top five labeled.



## M&As and IPOs

There is growing interest to understand deeper trends in AI Investments. Are M&A, Minority Stake, and Public Offerings equally as big as private investment? The chart below (Figure 4.2.7) plots the volume of different types of investment activity over time. It shows that VC-driven private investment accounted for about half of total investments in AI in 2019, with M&A and Public Offerings taking taking the major share of the remaining half. However, private investment accounted for 92% of the number of deals, with M&A making up just over 4% of deals, and Minority stakes and Public offerings (IPOs) together accounting for 3%. We note that Alibaba's IPO in 2014 accounts for the significant volume of IPO investment in 2014.

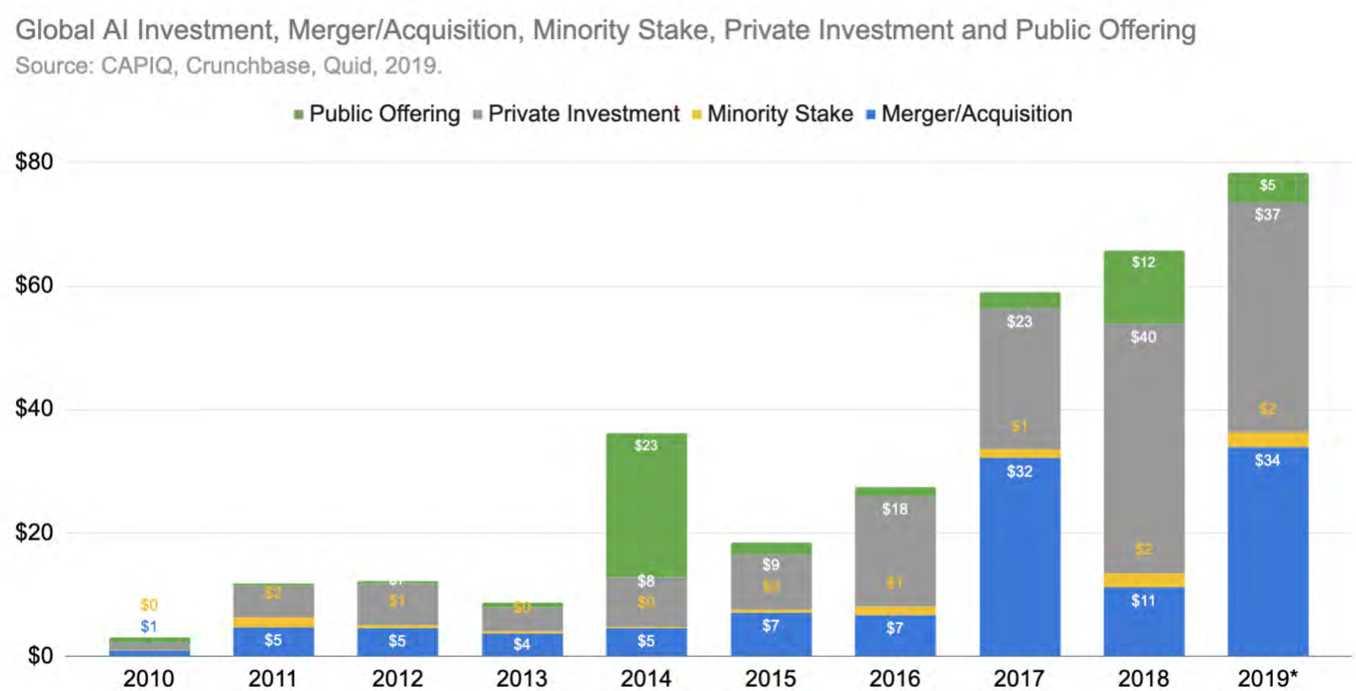



Fig. 4.2.7.
Note: y-axis in billions of US$.* 2019 data is until October, 2019. The jump in 2014 Public Offering reflects Alibaba's IPO.

**Mergers & Acquisitions in AI and corporate investment in AI are equally important vehicles for financing AI products and services.**

[Investment_Activity_Technical_Appendix]
[Access_Data]

## Public Investment

This section considers AI-related public investment for the US only. Reliable cross-country measures on public investment are difficult to obtain since they are no standards in measuring AI investment. Data from Bloomberg Government shows proxy estimates for the Department of Defense (DoD) budget estimates and Contract Spending across US government agencies. Considering federal civilian agencies and DoD budget estimates, the US federal government is projected to invest $4.98 billion in AI R&D in fiscal 2020.

**Federal Civilian Agencies' Budgets**

In February 2019, the White House issued an executive order that directed US government agencies to, for the first time, quantity their total AI investment and benchmark AI spending year-to-year. In September 2019, the National Science & Technology Council announced that federal civilian (non-Defense Department) agencies expected to invest $973 million on AI, according to a report supplementing the President's Fiscal 2020 Budget Request. The National Science Foundation is the largest civilian funder of AI, with $488 million budget for AI R&D in fiscal 2020, followed by the National Institutes of Health ($203 million), the Department of Energy ($163 million), and the Food and Drug Administration ($39 million). Figures on Defense Department AI R&D were withheld from the report for national security reasons.

**Department of Defense (DoD) Budget**

The Defense Department is projected to invest another $4.0 billion on AI R&D in fiscal 2020, according to an independent analysis by Bloomberg Government (Figure 4.2.8a). An analysis of the Pentagon's Fiscal 2020 Research, Development, Test & Evaluation (RDT&E) budget request yielded 346 unique budget line items that referenced AI-related keywords in their titles or descriptions. The Defense Advanced Research Projects Agency (DARPA) alone will invest $506 million in fiscal 2020, while the department will allocate $221 million to the Algorithmic Warfare Cross Functional Team, better known as "Project Maven." The cornerstone of the Pentagon's AI program, the Joint AI Center (JAIC), will receive $209 million.

Looking more closely at the DOD's RDT&E budget, the following graphs show the department's AI R&D budgets broken out by programmatic spending area and agency. Applied Research will receive the largest volume of funding ($908 million), followed by $821 million for Rapid Growth Advanced Component Development and Prototyping (ACD&P), and $398 Operational System Development (OSD) (Figure 4.2.8b). Rapid growth in these areas indicates that the Pentagon's focus is scaling and fielding AI prototypes in addition to basic and applied research.

The top AI funding entities within the DOD are the Office of the Secretary of Defense ($1.3 billion), which presides over the department's sprawling Research & Engineering (R&E) enterprise, DARPA ($506 million), and the military services, which collectively will invest $1.57 billion (Figure 4.2.8c).

Department of Defense (DoD) Fiscal 2020 Research, Development, Test & Evaluation (RDT&E) Budget, Artificial Intelligence-specific
Source: Bloomberg GOV, 2019.

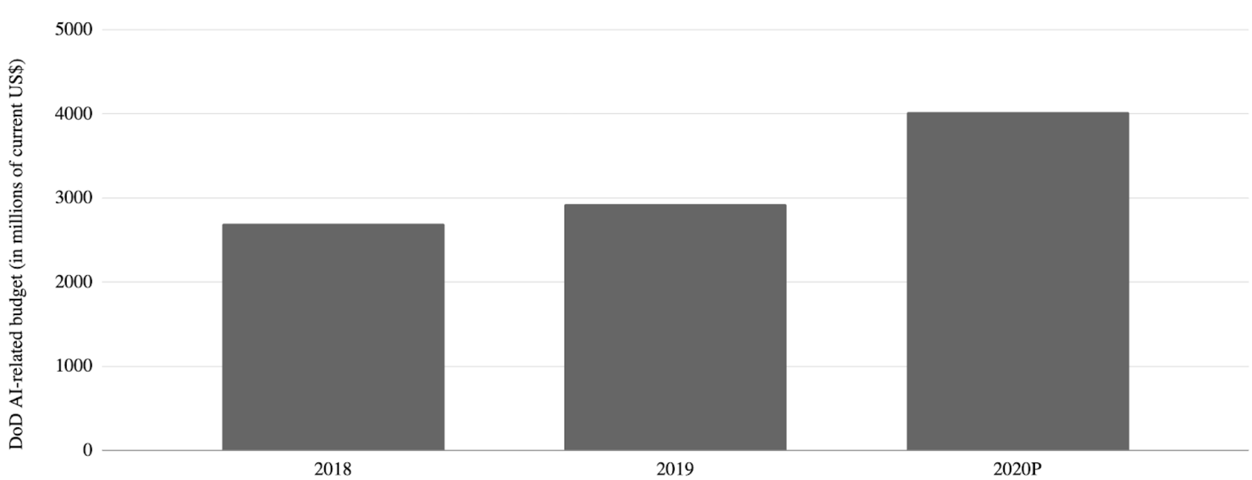



Fig. 4.2.8a.

## Public Investment

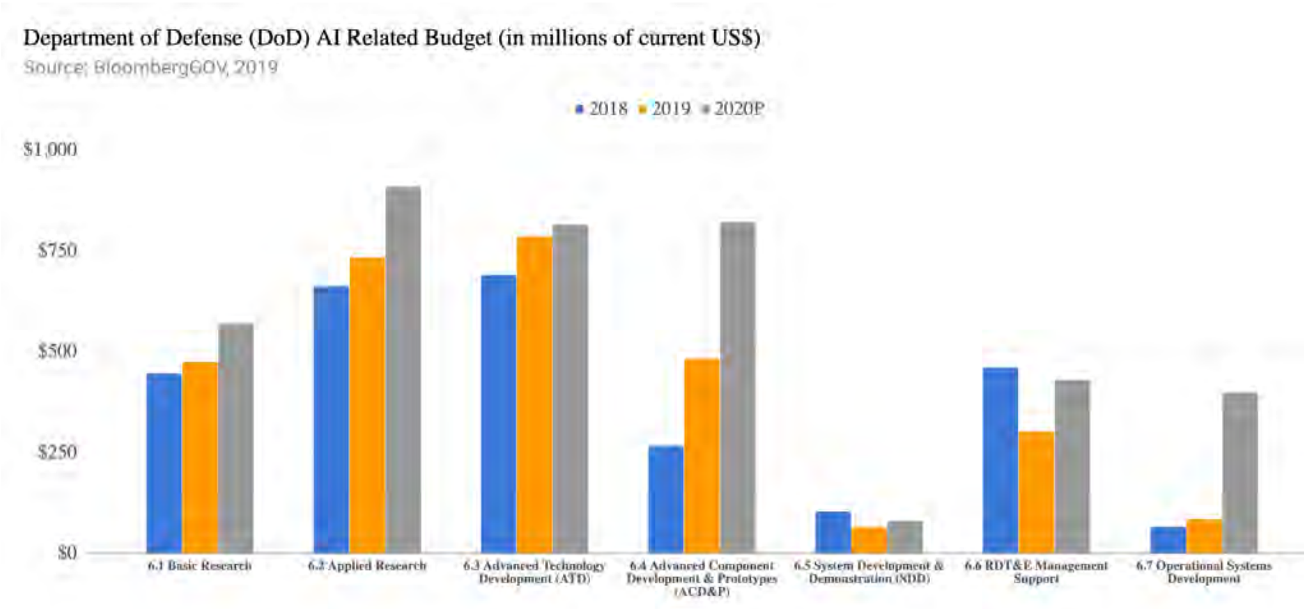



Fig. 4.2.8b.

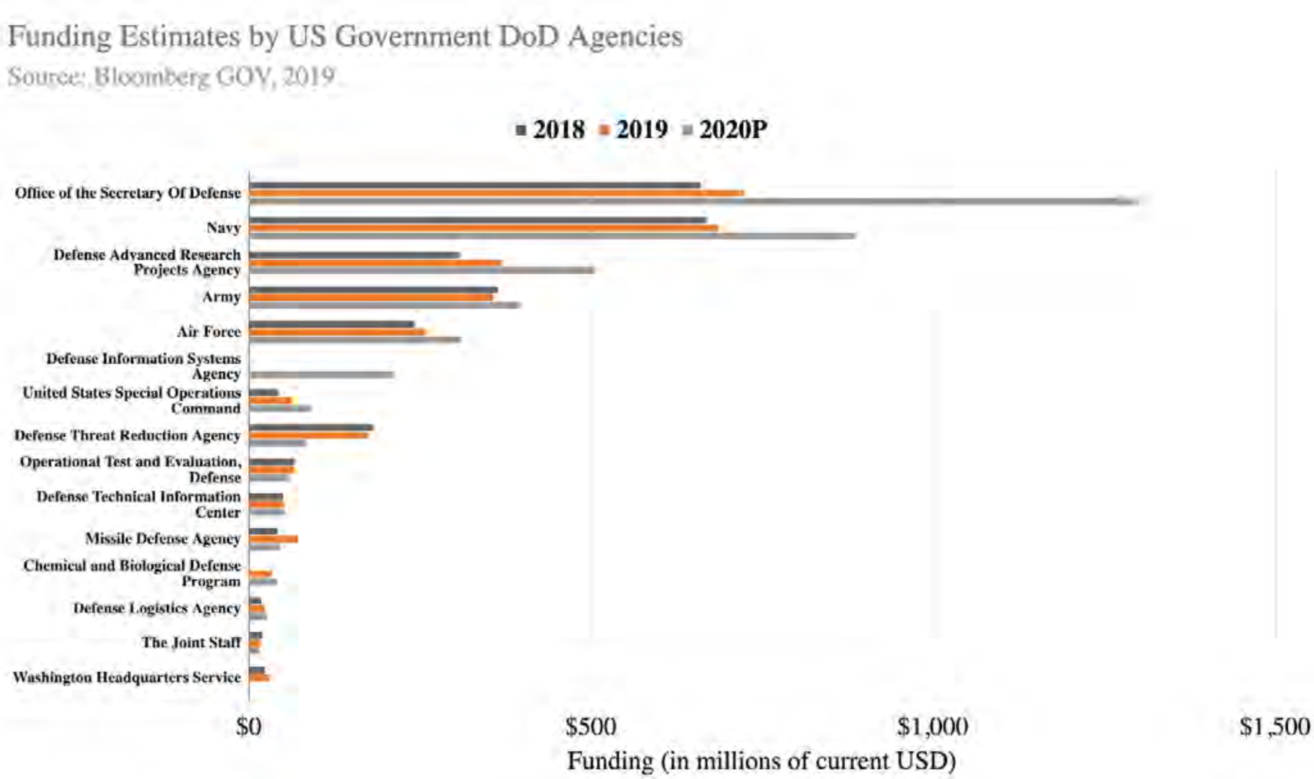



Fig. 4.2.8c.

## US Government Contract Spending

Another method of assessing public investment is studying the data on government contracts. The data (Figure 4.2.9a & 4.2.9b) below represents government spending transactions on AI projects between fiscal years 2000 to the present, as defined by Bloomberg Government. Bloomberg built its model using spending data reported by agencies to the [Federal Procurement Data System-Next Generation (FPDS-NG)](). To capture AI spending, Bloomberg first identified all spending transactions associated with R&D and IT projects (GSA Category Management Levels 1 and 17), then identified those that matched with a set of over 100 AI-related keywords (e.g., artificial intelligence, machine learning, neural network).

In fiscal 2018, the latest year in which complete contracting data is available, federal agencies spent a combined $728 million on AI-related contracts, an almost 70% increase above the $429 million that agencies spent in fiscal 2017. Since fiscal 2000, the Pentagon has accounted for the largest share of AI spending of any federal agency ($1.85 billion), followed by NASA ($1.05 billion), and the departments of the Treasury ($267 million) and Health and Human Services ($245 million).

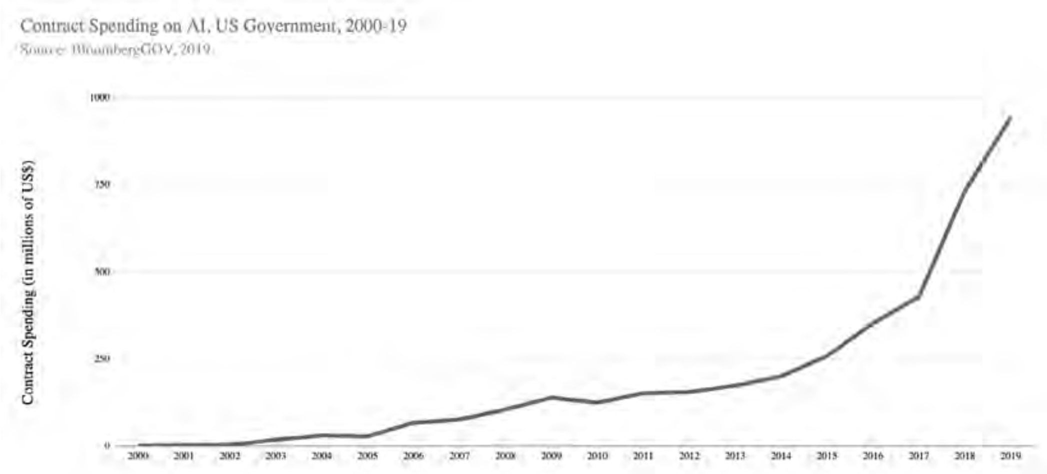



Figure 4.2.9a.

### Accounting for Contract Spending across all US Government Agencies

Source: Bloomberg Government based on contract analysis of over 200 government agencies

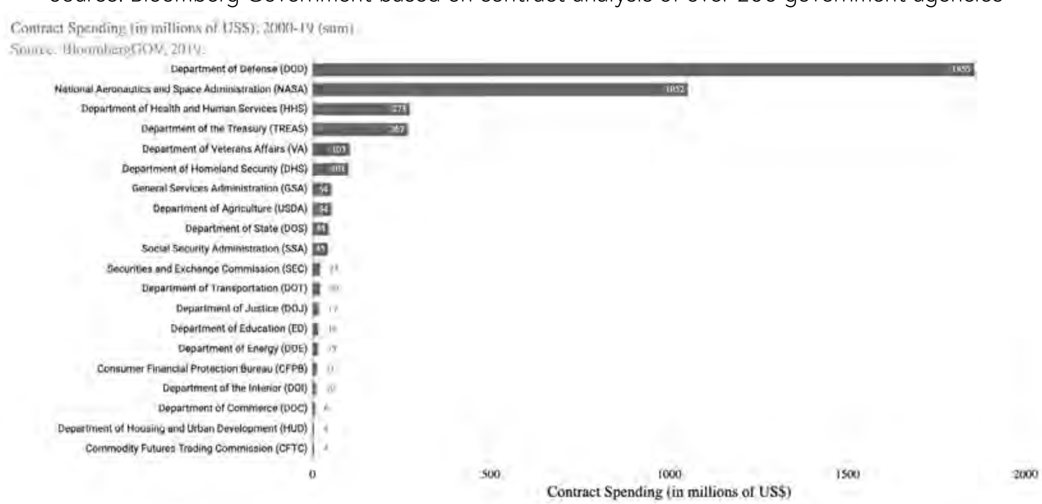



Figure 4.2.9b.

## Measurement Questions

- There is no standard consensus on labeling AI related investment activities. For example, startups that could be producers of new AI technologies, or consumers of AI, or others who are not actually involved in AI. It could be interesting to have a more standard labeling mechanism for AI VC investment, as well as corporate investment activities.

- Standard economic measurements can be applied to new data; however, accounting for AI in national accounting or balance of payments is an important discussion for national statistical agencies. There are no existing measurement and accounting standards for public investment or expenditure in artificial intelligence.

- Since AI is a technology that can be produced, transmitted, and consumed across borders, deeper data to uncover growing trading of AI across borders will be an important measurement question for policy decisions.

- Data on public investment is not consistently available across countries. The data here reflect public investments in the US While some data is available regarding announcements that some governments have made, how much of this has actually been invested is less clear. It will be important to continue to track such public investments.

## Industry Adoption

The graphs on the following pages show the result of a McKinsey & Company survey of 2,360 company respondents, each answering about their organizations. The full results of this survey, which include insights about how high-performing companies have adopted AI, the capabilities required to scale AI across the business, and the financial outcomes that companies have experienced by adopting AI, are published in McKinsey & Company's "Global AI Survey: AI proves its worth, but few scale impact."

### AI adoption by organizations is increasing globally

The results suggest a growing number of organizations are adopting AI globally. Fifty-eight percent of respondents report that their companies are using AI in at least one function or business unit#, up from forty-seven percent in 2018 (Figure 4.3.1a). Adoption appears to be more equally distributed across regions than in 2018, with about six out of ten respondents in most regions reporting their organizations have embedded AI. Across regions, respondents in developed Asia–Pacific report the largest growth since 2018, with a 19-percentage-point increase in companies embedding AI in at least one business function or business unit.

AI adoption *within* businesses has also increased. Thirty percent of respondents report that AI is embedded across multiple areas of their business, compared with 21 percent who said so in 2018 (Fig 4.3.1b).

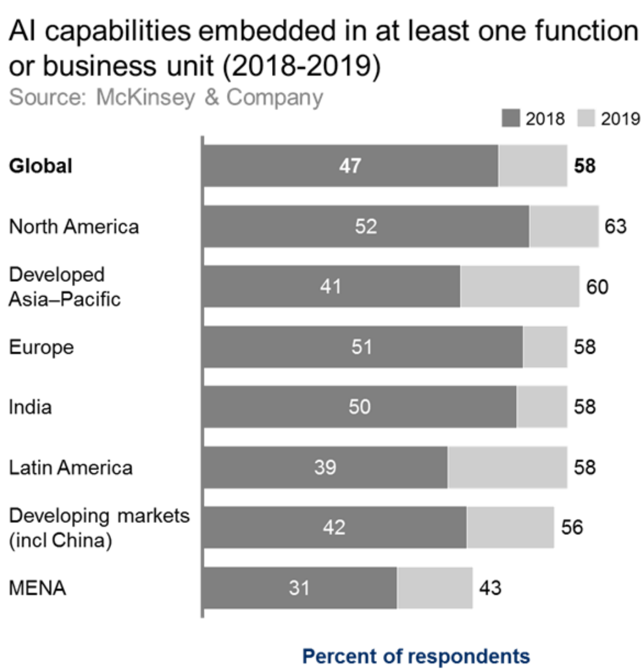



Fig. 4.3.1a.

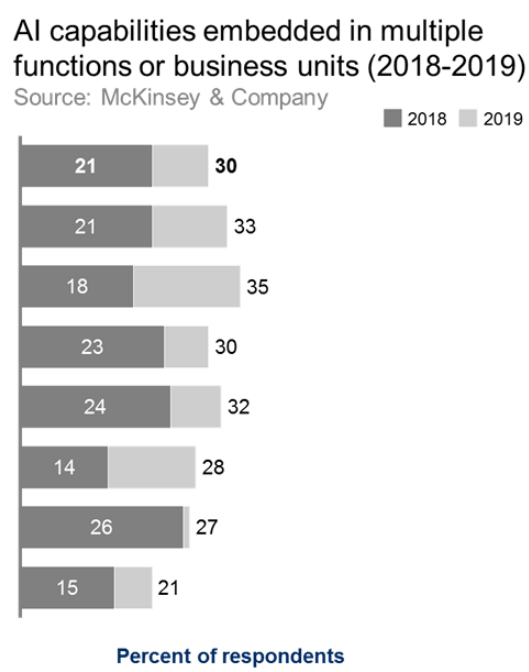



Fig. 4.3.1b..

## Industry Adoption

**Organizations adopt AI in business functions that provide most value in their industry**

Continuing the trend of 2018, companies are most likely to adopt AI in functions that provide core value in their industry (Figure 4.3.2).

For example, respondents in the automotive industry are the most likely to report adoption of AI in manufacturing, and those working in financial services are more likely than others to say their companies have adopted AI in risk functions. Telecom companies are most often adopting AI in service operations, while companies in the pharmaceutical industry tend to apply AI in product development and manufacturing. Respondents in consumer-packaged goods, travel and logistics, and retail are the most likely to report adoption of AI in supply-chain management.

AI adoption by industry and function (2019)

Source: McKinsey & Company

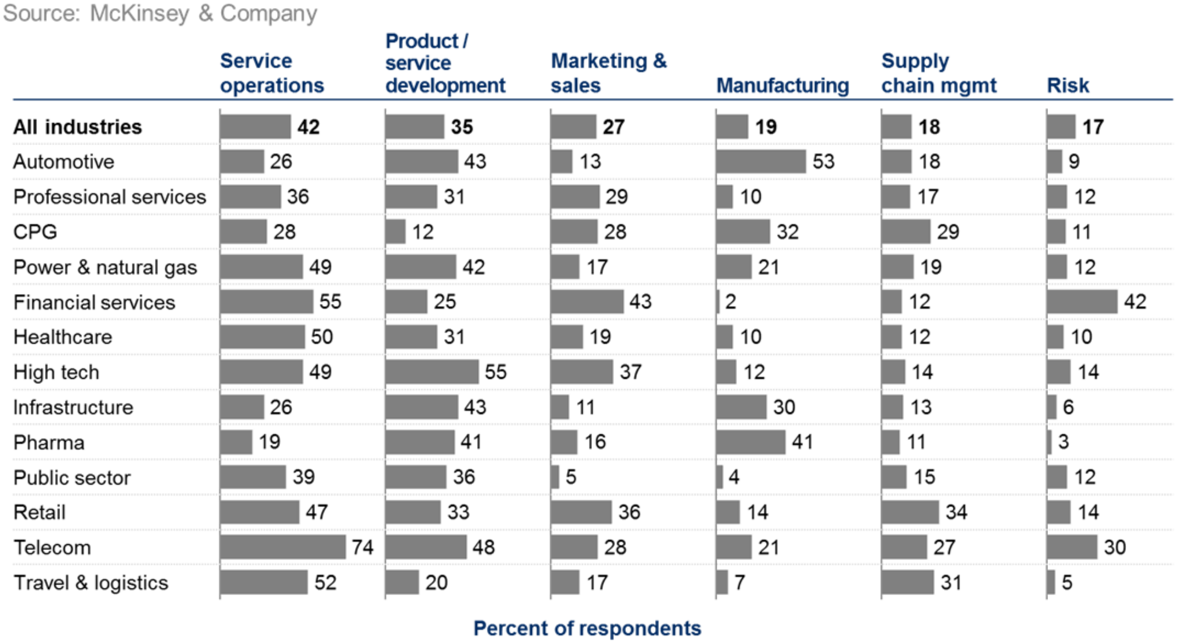



Fig. 4.3.2.

## Industry Adoption

**The AI capabilities that organizations adopt differ significantly by industry**

Across industries, respondents are most likely to identify robotic process autmation, computer vision, and machine learning as capabilities embedded in standard business processes within their company (Figure 4.3.3). However, the capabilities adopted vary substantially by industry.

For example, natural language capabilities—including both understanding and generation of natural language text and speech—are adopted most often in industries with large volumes of customer or operational data in text form, including high tech, telecom, retail, financial services, and healthcare. By contrast, physical robotics is most frequently adopted in industries where manufacturing or transport of physical goods plays an important role in the supply chain, including automotive, consumer packaged goods, and pharma.

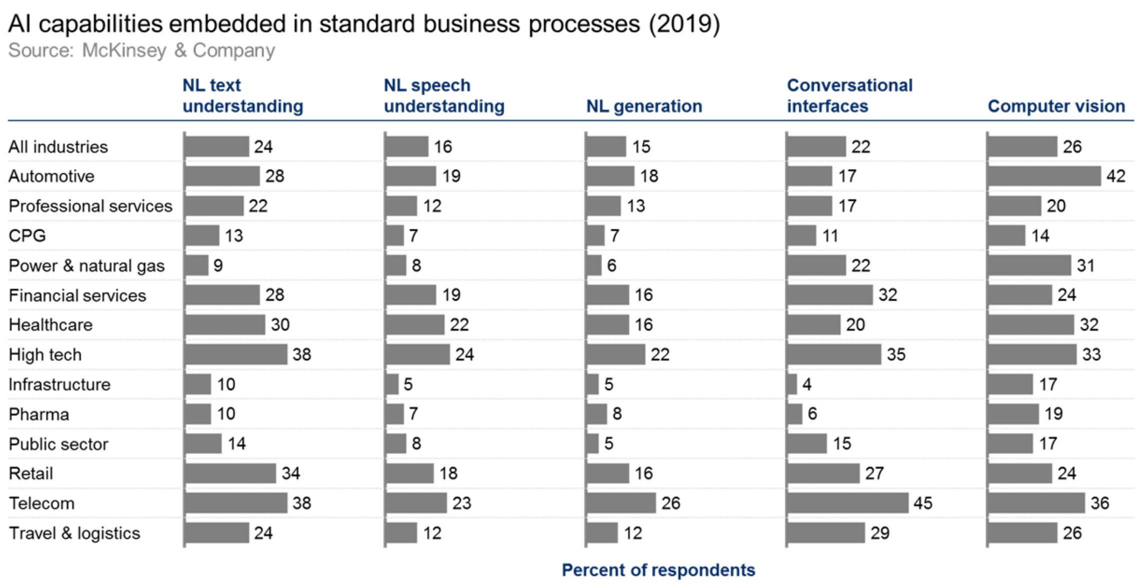



Fig. 4.3.3a.

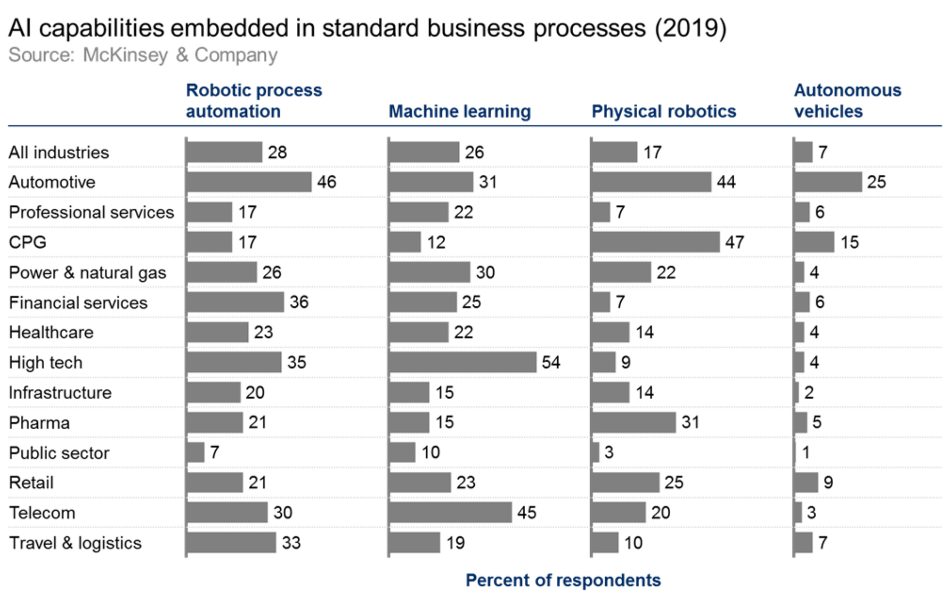



Fig. 4.3.3b.

## Industry Adoption

**Many companies applying AI do not report taking steps to mitigate the risks**

McKinsey's study surveyed respondents on ten of the most widely recognized risks related to AI, including regulatory compliance, equity and fairness, cybersecurity, and personal and individual privacy.

Cybersecurity is the risk respondents most often say their companies are mitigating, cited by 48 percent of respondents from companies that have adopted AI. Thirty-five percent say their organizations are taking steps to mitigate risks associated with regulatory compliance, and three in ten say the same about personal and individual privacy.

Despite growing recognition of the importance of addressing ethical concerns associated with usage of AI, only 19 percent of respondents say their organizations are taking steps to mitigate risks associated with explainability of their algorithms, and 13 percent are mitigating risks to equity and fairness, such as algorithmic bias and discrimination (Figure 4.3.4).

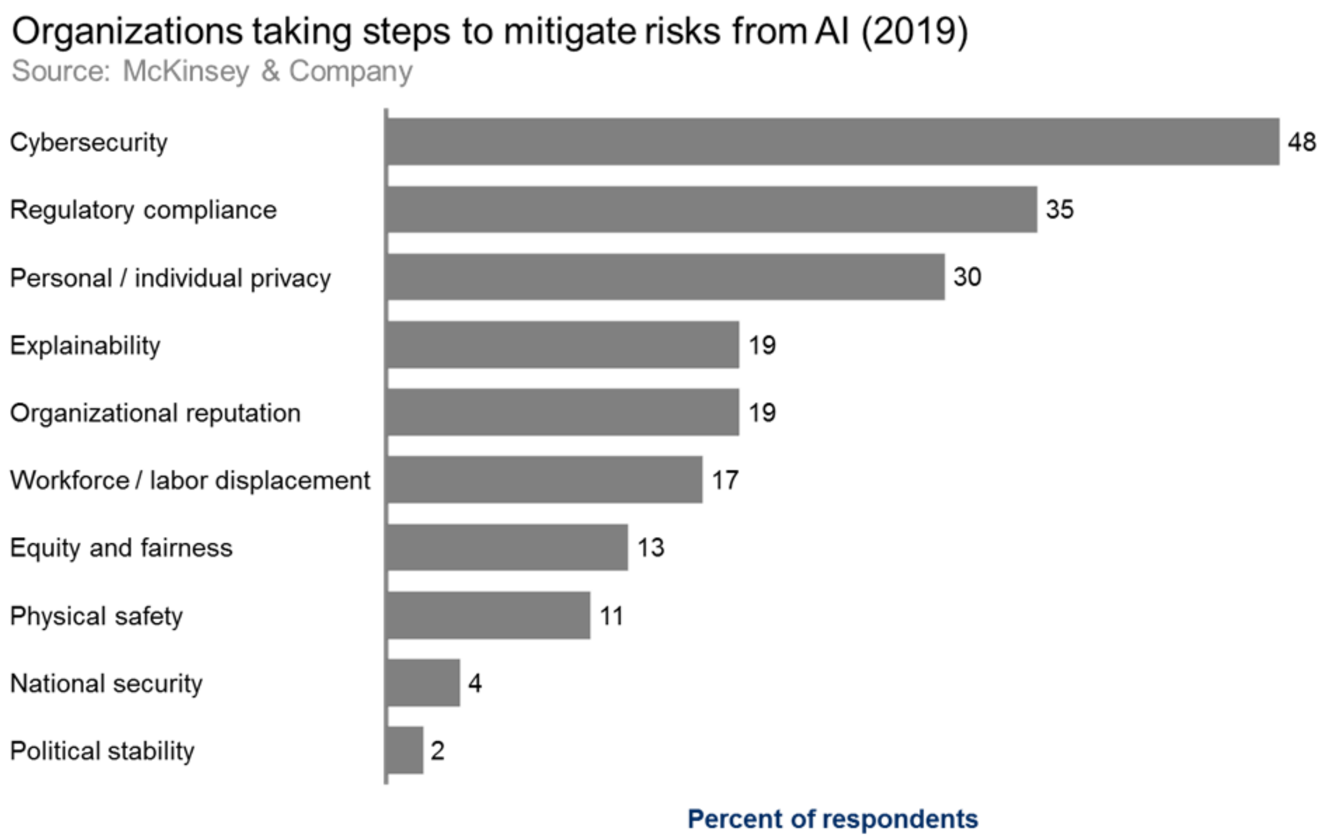



Fig. 4.3.4.
Note: Respondents who said "don't know / not applicable" are not shown.

## Robot Installations

The graphs below show annual installations of industrial robot units for the world (Figure 4.3.5). In 2018, global robot installations increased by 6% to 422,271 units, worth USD 16.5 billion (without software and peripherals). The International Federation of Robotics (IFR) computed the operational stock of robots at 2,439,543 units (+15%). The automotive industry remains the largest customer industry with 30% of total installations, ahead of electrical/electronics (25%), metal and machinery (10%), plastics and chemical products (5%) and food and beverages (3%).[11] As mentioned in earlier AI Index Report, the numbers do not provide any indicator on how many of the systems actually use any means of AI, however they provide a measurement of installed infrastructure susceptible of adopting new AI technologies.

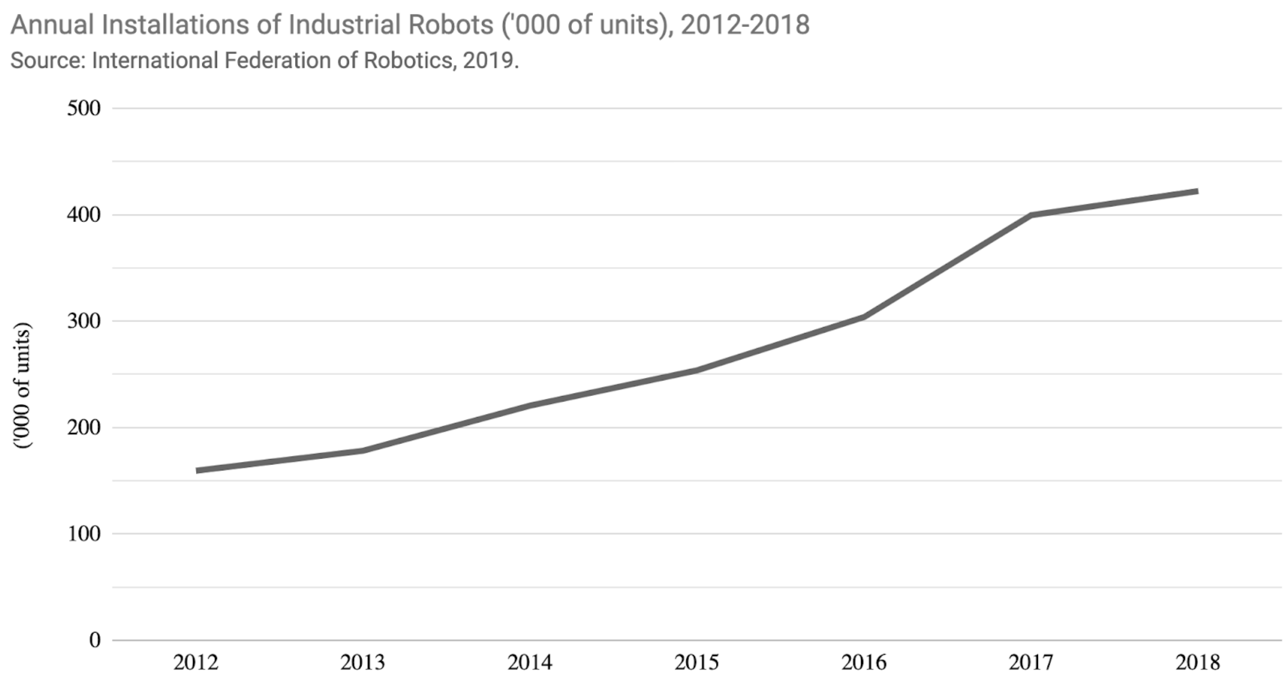



Fig. 4.3.5.

## Global Robot Installations in 2018 more than 400,000 units

[11] Note that for almost 20% of the robots there is no information on the customer industry.

## Robot Installations

The five major markets for industrial robots are China, Japan, the United States, the Republic of Korea, and Germany (Figure 4.3.6). These countries account for 74% of global robot installations. Since 2013, China has been the world's largest industrial robot market with a share of 36% of total installations in 2018. In 2018, 154,032 units were installed. This is 1% less than in 2017 (156,176 units) but still more than twice the number of robots installed in Europe and the Americas together (130,772 units). The main industries using robots in China are Electronics, Automotive & Metals, and the main application areas for industrial robots are handling and welding. Collaborative robots remain a small share compared to traditional industrial robots (Figure 4.3.7).

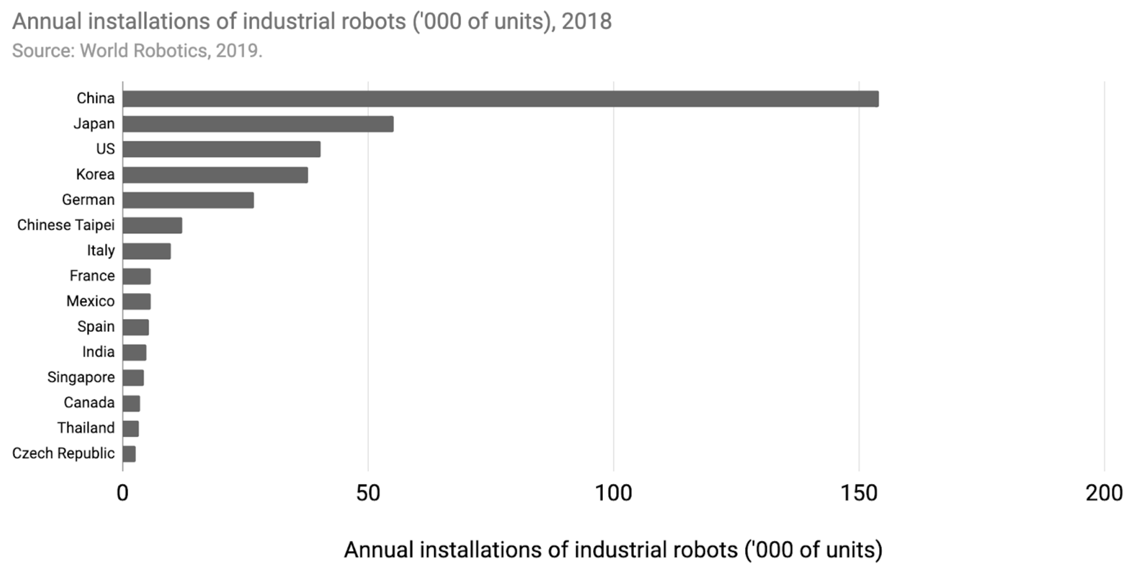


Fig. 4.3.6.

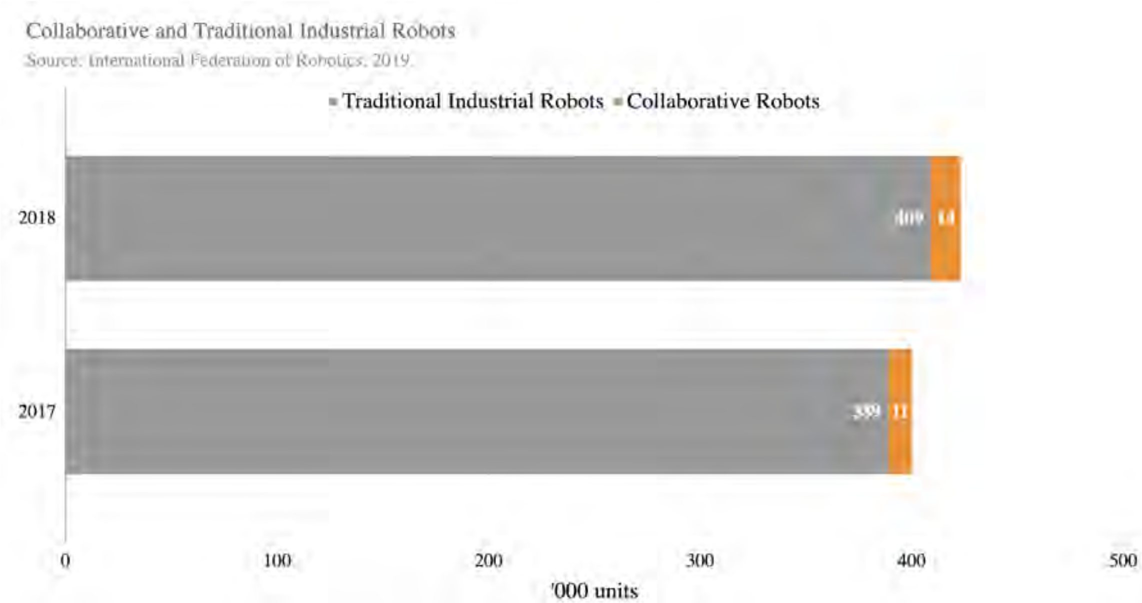


Fig. 4.3.7.

**74% of global robot installations concentrated in five countries**

## Measurement Questions

- Additional firm-level data would be helpful to understand the impacts of AI adoption on firm performance. It would also be valuable to measure the availability and concentration of inputs for AI applications, including data available to countries or to firms, compute power, and talent, to improve understanding of the impact on competition and market power.

- From an economic lens, it would be invaluable to understand the AI components of robotics. Equally important are national and international statistical data on trade flows (imports and exports) of industrial versus service robotics, as a sector in labor force and enterprise surveys. There is also a need to understand the income inequality consequences of robotic automation.

- From a technical performance perspective, it would be essential to measure progress in specific robot tasks (from elementary to complex tasks) in a standardized manner. As observed by Rodney Brooks in the 2018 AI Index Report many sources quote industrial robot shipments that have very little (or no) AI in them, which makes it a poor metric for progress in AI. It could be interesting to look at robots which have an AI component, such as drones (which use SLAM, and other AI algorithms) distinct from home robots such as Roomba, that also have an AI components. Could we identify AI components in distinct robotic systems, and associated failure rates, in addition to their global adoption?

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# Chapter 5: Education

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[Education_Technical_Appendix]

# Introduction

This chapter presents trends in AI education from a variety of data sources, starting first with global data from Coursera and Udacity ML and AI training courses. Second, trends in undergraduate enrollment in introductory ML and AI courses are presented for the US and international universities. Programs from European countries are also identified based on data from Joint Research Center, European Commission and the trends in AI PhD specialization for North America based on the CRA Taulbee Survey. Third, trends in PhD hires on industry hiring, faculty hiring and faculty departures are presented based on the Taulbee Survey and Goffman and Jin (2019). Fourth, trends in gender and international diversity for AI PhDs are presented, along with faculty diversity across select university departments. Included here is a short discussion on ethics courses in computational programs.

It is important to note that there are many other kinds of diversity. The Index continues to gather more numbers on underrepresented minorities, gender minorities, and other groups for 2020.

## Coursera

**Online Learning**

Increasingly, AI education extends beyond the brick and mortar university. Online learning plays a key role in educating and developing AI skills in the workforce around the globe. Many questions arise about what skillsets students gain, where, and how they are meeting demands.

**Coursera**

Coursera, the world's largest online platform for higher education, serves over 45 million learners around the world by providing access to high quality content from leading universities and companies. The scale of the platform, which includes 3,700+ courses, 400+ specializations, and 16 degrees, creates one of the largest skills databases as millions of learners take graded assessments ranging from multiple choice exams to programming assignments to peer reviewed projects that measure their skill proficiency.

The Coursera Global Skills Index (GSI) ddraws upon this rich data to benchmark 60 countries and 10 industries across Business, Technology, and Data Science skills to reveal skills development trends around the world.

Cousera measures the skill proficiency of countries in AI overall and in the related skills of math, machine learning, statistics, statistical programming, and software engineering. These related skills cover the breadth of knowledge needed to build and deploy AI powered technologies within organizations and society:

•**Math:** the theoretical background necessary to conduct and apply AI research
•**Statistics:** empirical skills needed to fit and measure the impact of AI models
•**Machine Learning:** skills needed to build self learning models like deep learning and other supervised models that power most AI applications today
•**Statistical Programming:** programming skills needed to implement AI models such as in python and related packages like sci-kit learn and pandas
•**Software Engineering:** programming skills needed to design and scale AI powered applications

Below is a world heat map that shows the AI proficiency rankings of the 60 countries covered in the GSI (Figure 5.1). The map shows the quartile ranking category of each country denoted by cutting edge (76%-100%), competitive (51%-75%), emerging (26%-50%), and lagging (0%-25%). Details on the construction of these AI rankings is provided in the Technical Appendix along with a sample skills taxonomy that shows the breakdown of AI skills.

For each major geographic region, you can also see the average country's share of enrollments in AI and the five related competencies (Figure 5.2). The enrollment trends show that South Asia followed by East Asian countries tend to have a higher share of enrollments in AI and related skills.

Note that in terms of country size, there is not a strong correlation between number of users on Coursera and the skill rank of a country in AI. Rather the skill rank of a country correlates much more strongly with metrics like a country's GDP per capita and the level of investment in tertiary education. See this article for some plots. In addition, the rankings are robust to adjusting for self selection in using Coursera through propensity score weighting.

*"The Fourth Industrial Revolution is upon us, foreshadowing massive changes to the nature of work. Without a concerted focus on skill development, the dislocations will be widespread and felt most acutely by the poorest and least educated. Keeping pace with the fundamental market shifts will demand coordinated investments in skill development — not just by individuals, but also by companies and governments around the world." —*
Emily Glassberg Sands and Vinod Bakthavachalam (Coursera Data Science)
*Harvard Business Review*

## Coursera

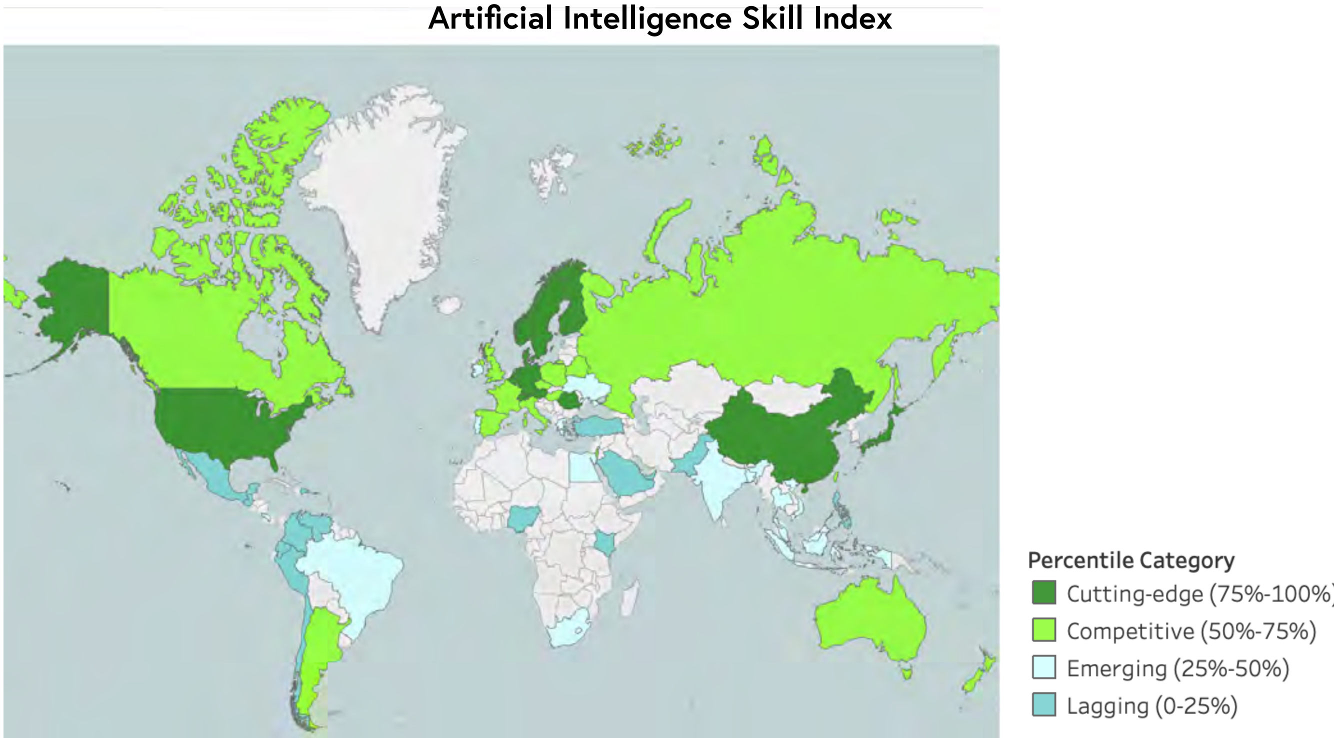



Fig. 5.1.

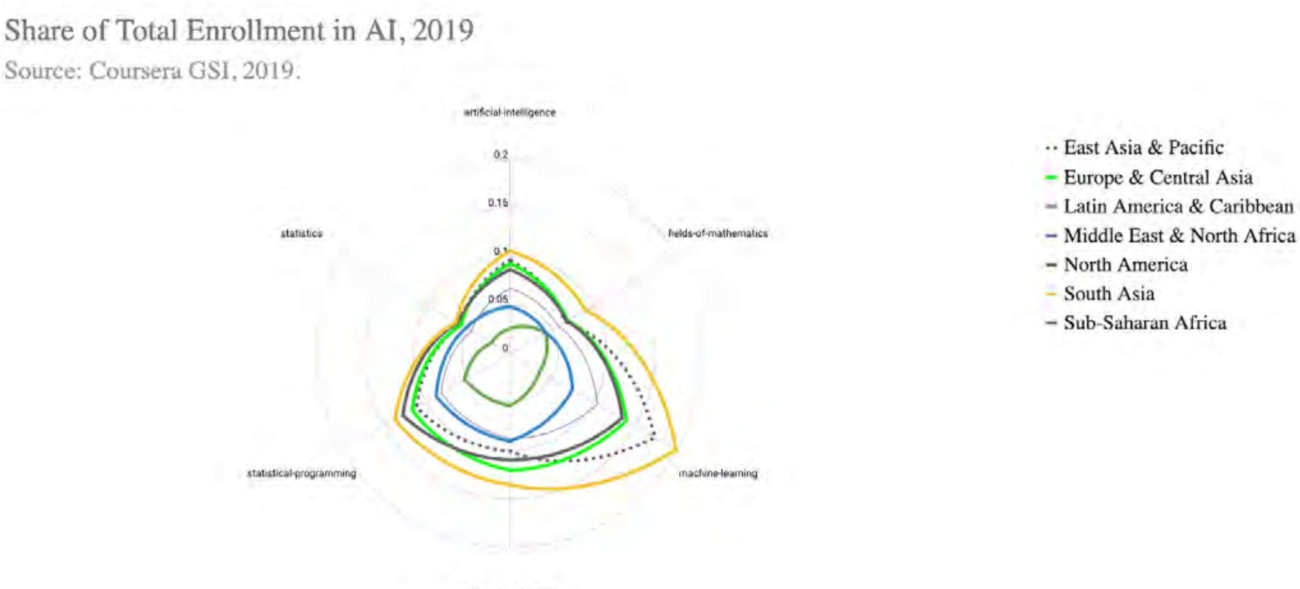



Fig 5.2.

## Udacity

The enrollment in different AI specialization courses on Udacity is presented next (Figure 5.3). The chart shows the running total enrollment in the various AI specializations for Udacity AI specialization courses. *Introduction to TensorFlow for Deep Learning* has maintained the highest total enrollment till mid-2019. However, *Introduction to Machine Learning* has cumulatively the highest enrollment number in later 2019, with over 125,000 cumulative global enrollment. *Introduction to AI* is close behind, followed by more computer systems engineering topics such as *Introduction to Hadoop and MapReduce*.

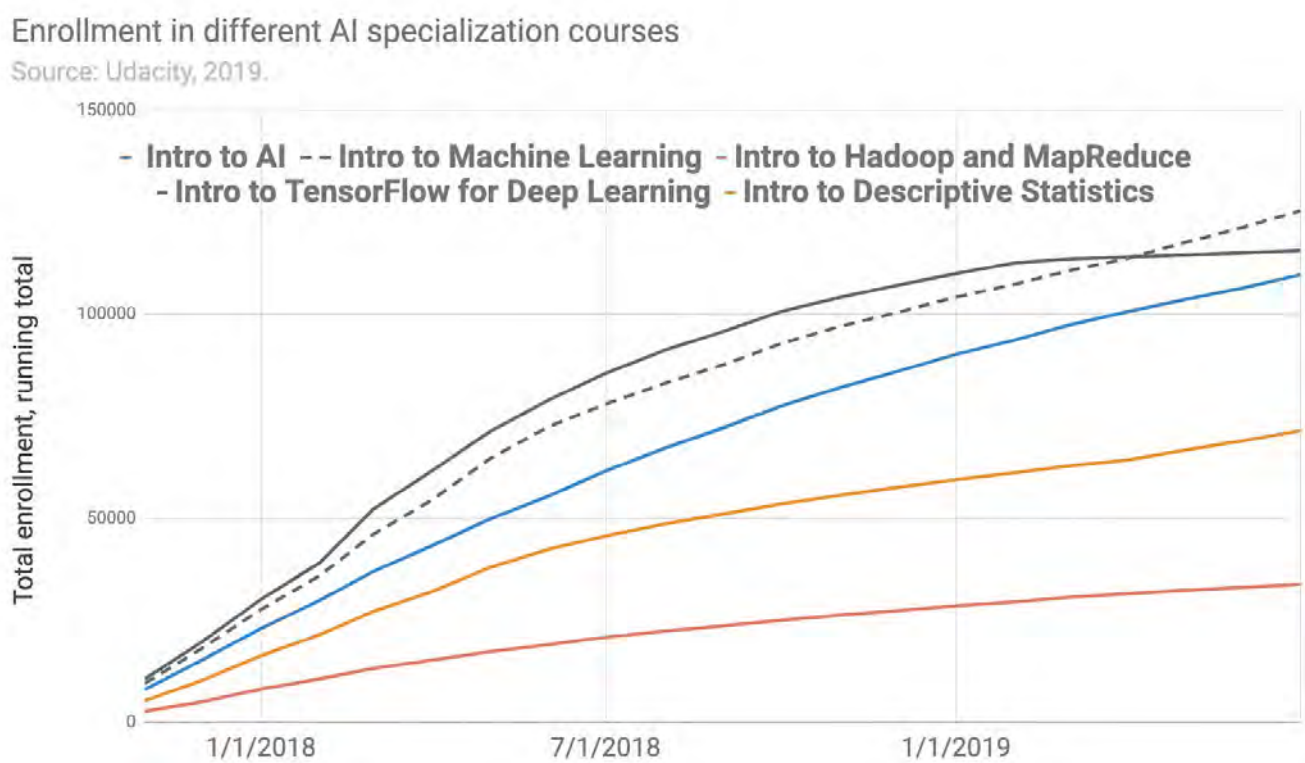



Fig. 5.3.

## US Course Enrollment

The graphs below (Figures 5.4a & 5.4b) show the number of students enrolled in introductory AI and ML courses in a number of US universities. School selection criteria, actual enrollment numbers, and full university names can be found in the appendix. Enrollment in *Introduction to Artificial Intelligence* grew five-fold between 2012 and 2018 at Stanford University. Enrollment in *Introduction to Machine Learning* grew 12-fold between 2010 and 2018 at the University of Illinois at Urbana-Champaign (Figure 5.4c & Figure 5.4d). Some schools indicated that growth in enrollment was limited by availability of classes, so these graphs may underrepresent the real demand for these courses.

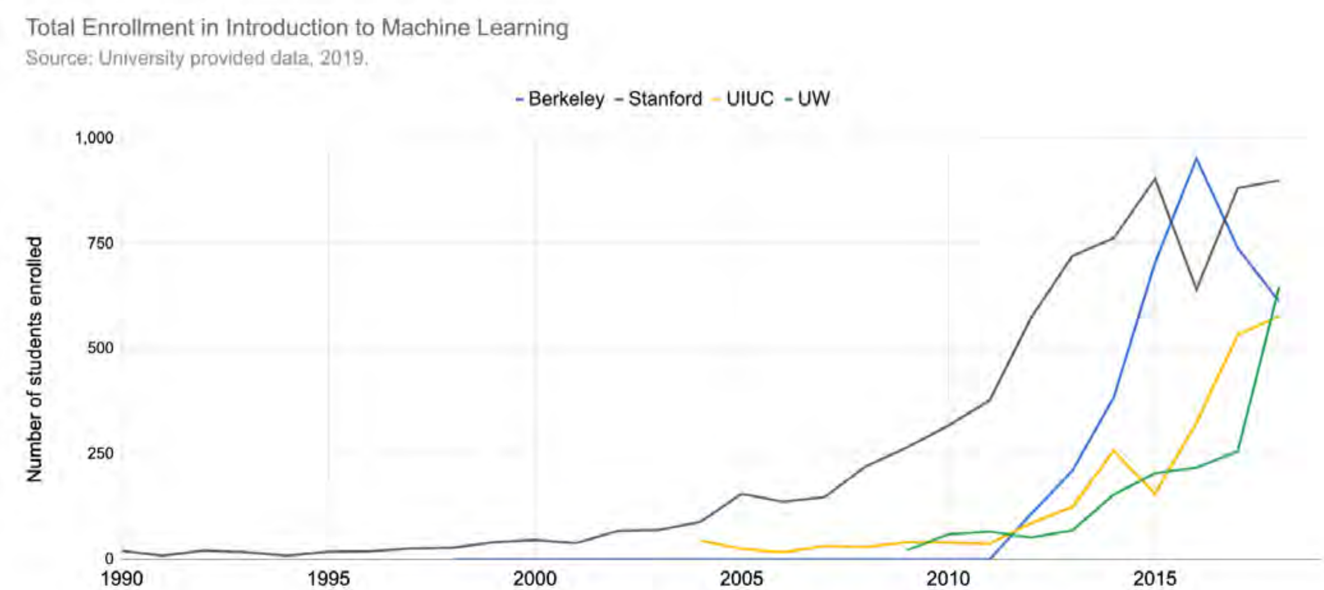



Fig. 5.4a.

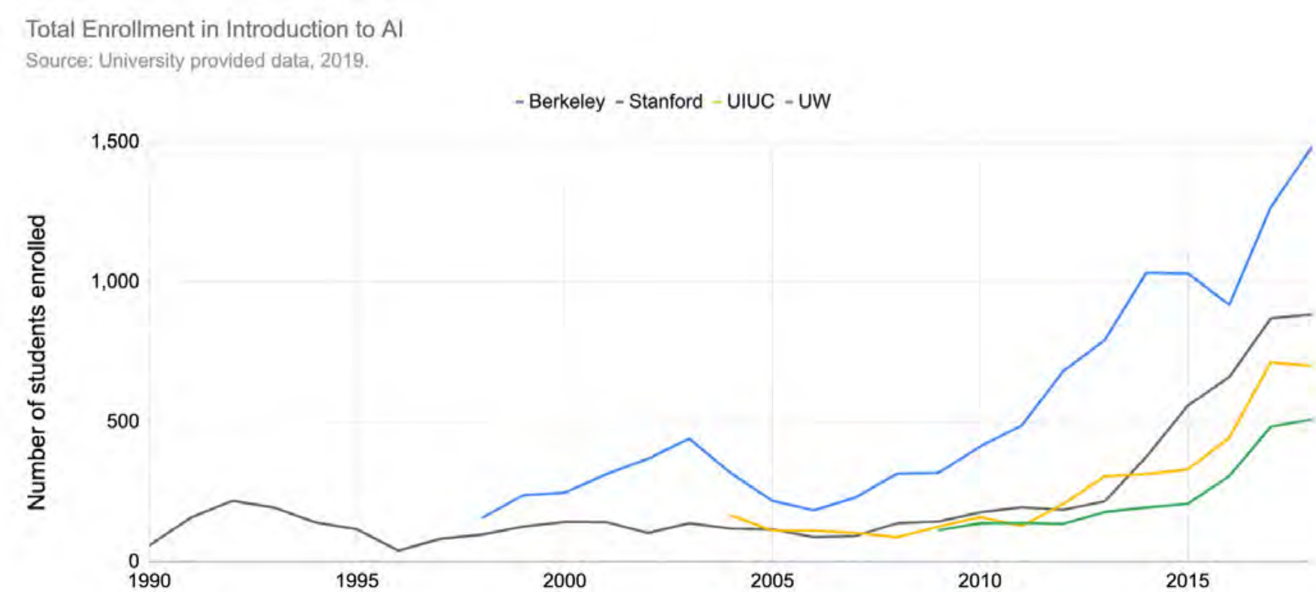



Fig. 5.4b.

## US Course Enrollment

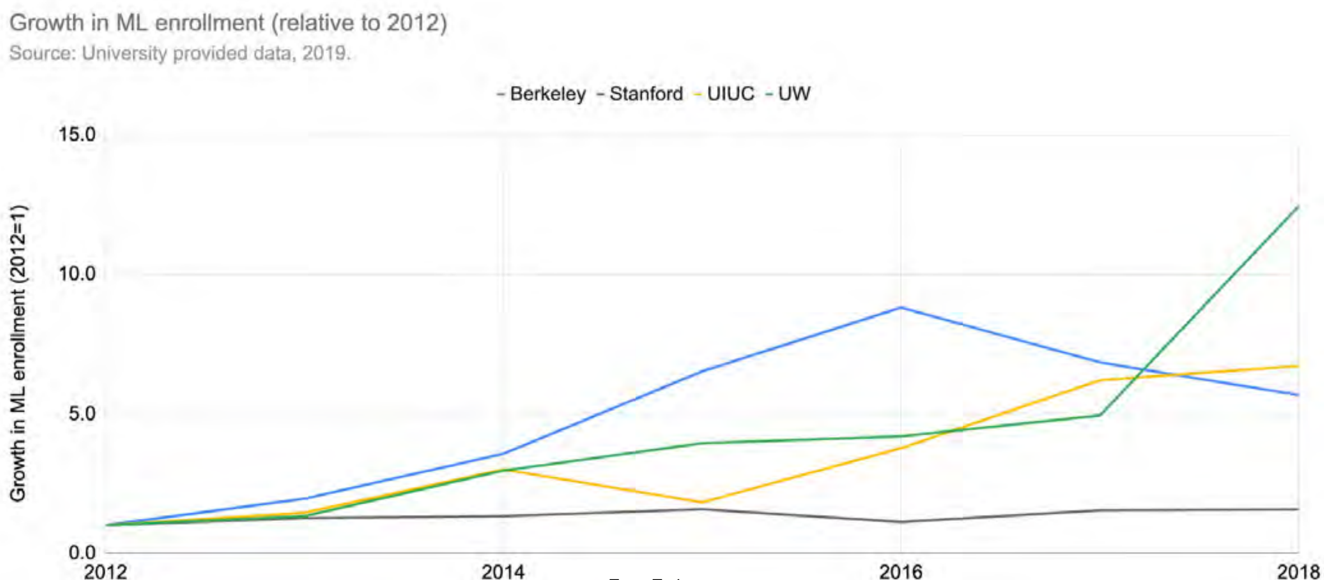



Fig. 5.4c.

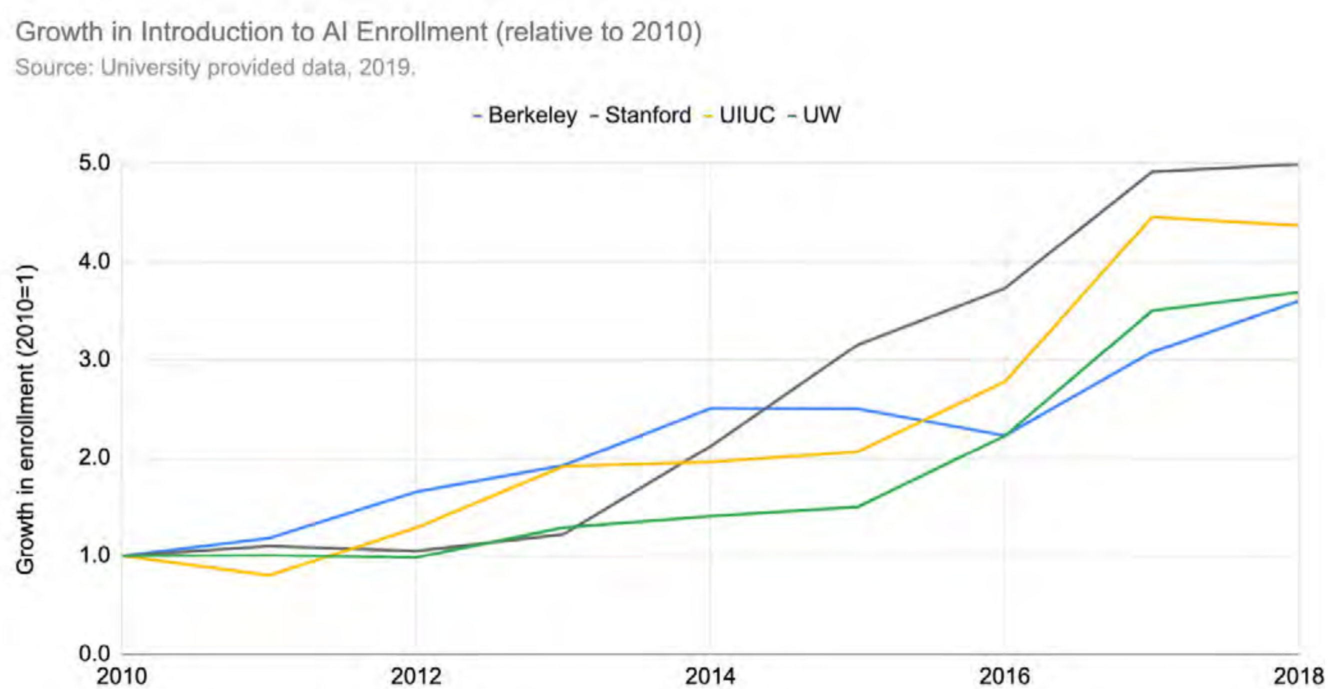



Fig. 5.4d.

## International Courses

The graphs below (Figure 5.5a) show AI and ML course enrollment at several leading computer science universities outside of the US The graph shows relative growth for international schools that provided data for academic years 2010 — 2019. School selection criteria, actual enrollment numbers, and full university names can be found in the appendix. In the given sample, the University of Toronto (Canada) has the highest number of registered students for Introduction to AI+ML, followed by High School of Economic (Russia), and Tsinghua University (China) in 2018. Relative to 2015, enrollment has grown four-folds at Tsinghua University, three-folds at University of Toronto, and doubled at University of Melbourne (Figure 5.5b).

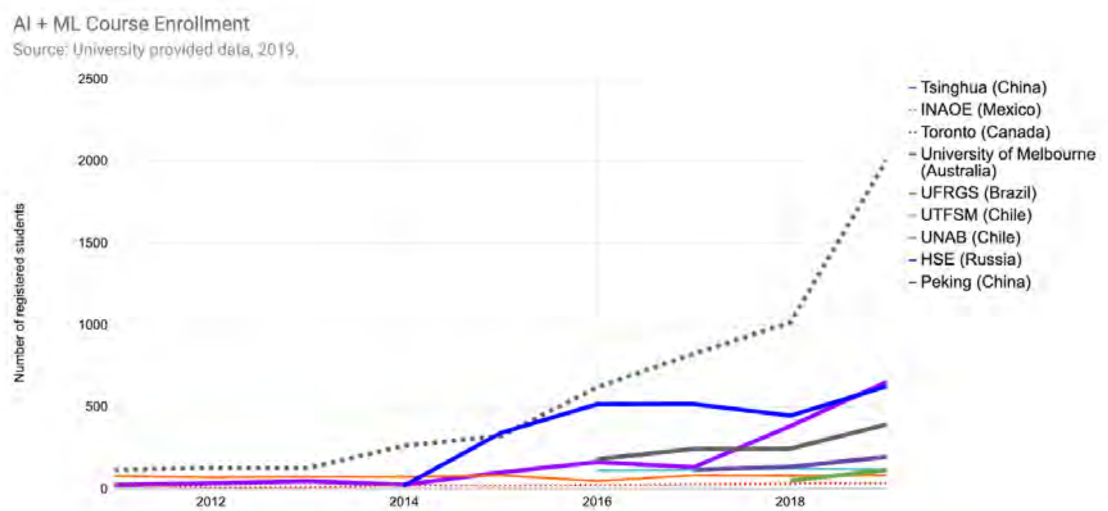



Fig. 5.5a.

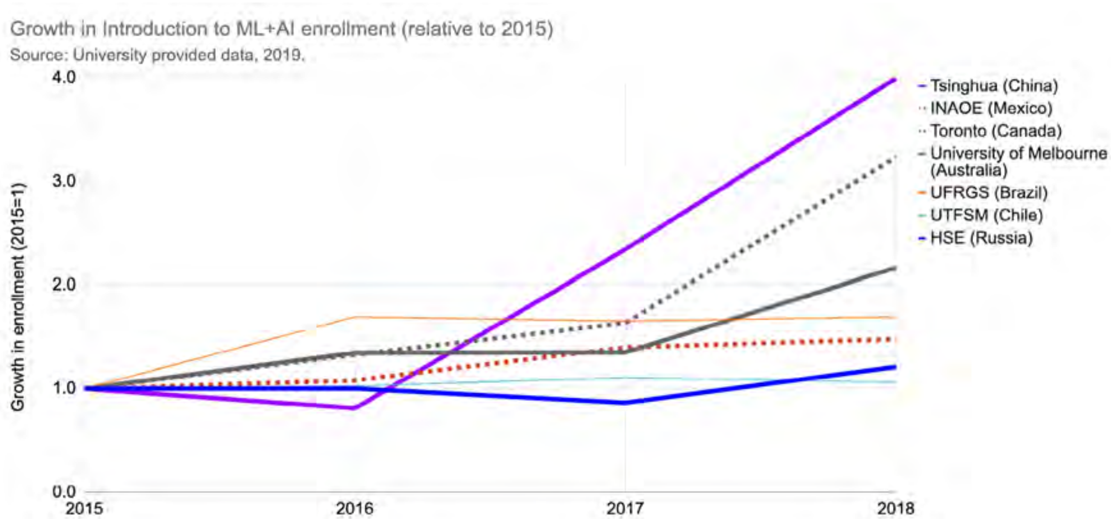



Fig. 5.5b.

**Across the schools studied, we found that growth in AI course enrollment was relatively school dependent, and was not particularly influenced by geography. The AI Index looks forward to refining this hypothesis in future reports.**

## Trends From Europe

Text mining and machine learning techniques were applied to all universities across Europe that have a website (as listed by the Webometrics initiative). The data related to the programs of study address the domains that have been identified by the Joint Research Centre (JRC), the science and knowledge service of the European Commission (EC). The data collection effort identified a suitable term of comparison when considering third party sources, to measure strengths and weaknesses of a (semi) automatic classification system for program content. Readers can refer to Academic offer and demand for advanced profiles in the EU for more technical details.

This data (Figure 5.5c) identified a total number of 2,054 programs covering the domain of Artificial Intelligence to differing extents. The vast majority of AI academic offerings in Europe are taught at the masters level, as the MS is the expected terminal degree and generally perceived as the most appropriate to acquire the needed advanced skills. The graph (Figure 5.5d) shows that there are 197 European universities offering a total of 406 specialized masters in AI; 84 of the universities, or 43%, offer at least 2 specialized masters in AI. Programs have been classified, depending on the level, into bachelors and masters. Though not exhaustive, the selected data source offers a perspective on the academic offerings targeting the selected domains in EU28.[12]

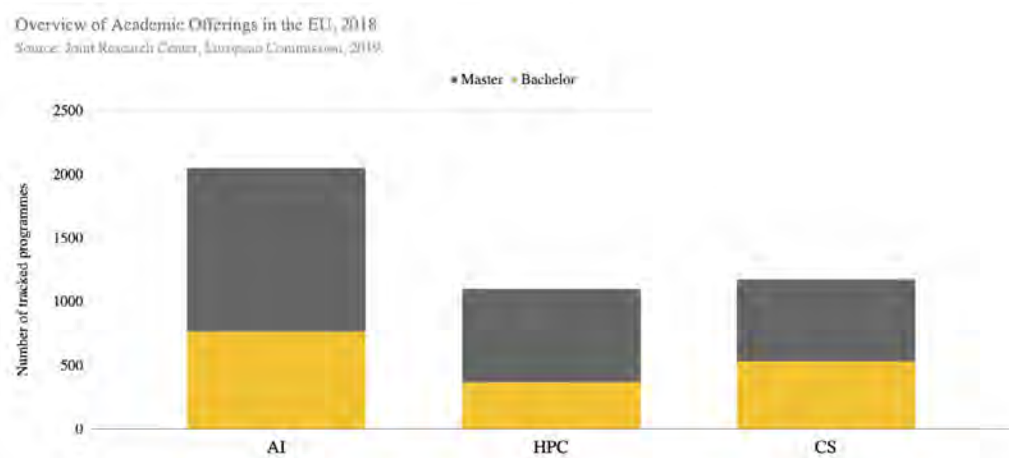



Fig. 5.5c.
Note: The total number of programmes in the selected domains does not correspond to the sum of programmes in each domain due to the fact that a programme may correspond to more than one domain.

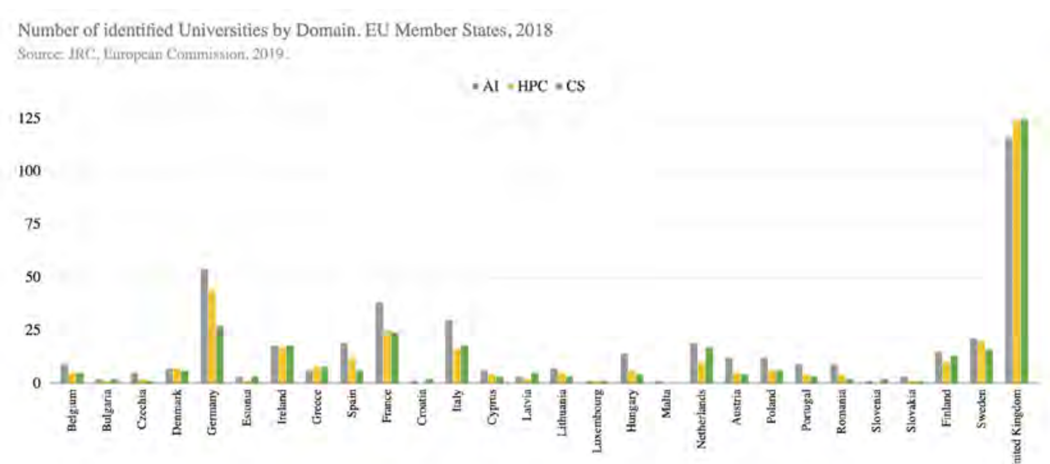



Fig. 5.5d.

[12] United Kingdom leads both in number of companies and of programmes offered by universities, hosting one third of AI companies and more than half of AI programmes. In 2016, countries employing highest number of ICT specialists were United Kingdom (1.7 million persons), Germany (1.5 million), France (1.0 million), Italy (721 thousands) and Spain (632 thousands).

## PhD Specialization in AI

The Computing Research Association's (CRAs) Taulbee Survey is conducted annually to document trends in student enrollment, degree production, employment of graduates, and faculty salaries in academic units in the US and Canada that grant the Ph.D. in computer science (CS), computer engineering (CE), or information (I). Only doctoral departments of computer science and computer engineering are included. Historically, Taulbee has covered 1/4 to 1/3 of total BS CS recipients in the US. The categorization of specialty areas changed in 2008 and was clarified in 2016. From 2004-7, AI and Robotics were grouped; since 2008, AI has been separate; in 2016 AI also included ML.

The first chart (Figure 5.6a) shows AI/ML PhD grad specializations as a percent of computing PhD graduates in the US (and the number of AI/ML graduating PhDs). It is more difficult to estimate the growth in AI/ML undergraduate specialization, but the appendix chart shows undergraduate enrollment in CS is over 130,000 in 2018.[13] The specialization of computing PhDs is presented next. The bar chart (Figure 5.6b) shows (a) the share of computing PhD grads in 2018 by areas of specialization, and (b) the changes in share of each specialization between 2010-18. AI is the most popular PhD specialization for computing PhD grads and continues growing the fastest. In 2018, over 21 percent of graduating computing PhDs specialize in Artificial Intelligence/ Machine Learning.

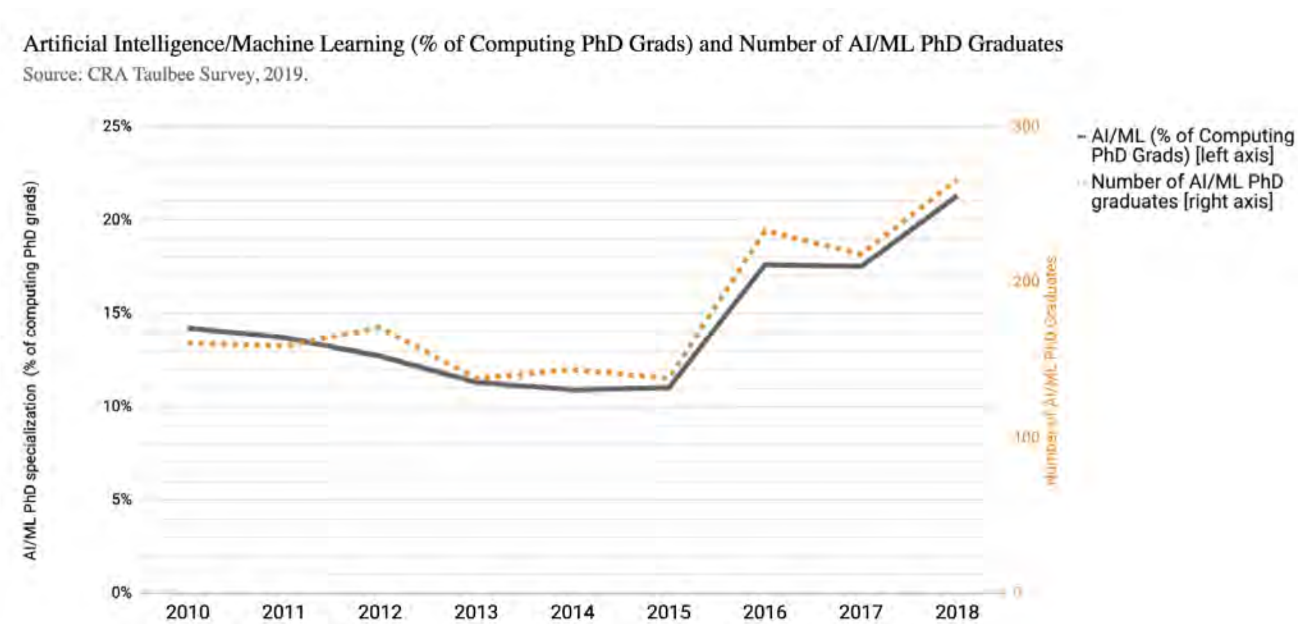



Fig. 5.6a.

**AI is the most popular area for CS PhD Specialization. In 2018, over 21 percent of graduating computing PhDs specialize in Artificial Intelligence/Machine Learning.**

[9] The number of students entering undergraduate enrollment (~34,000) exceed the number of undergraduates graduating (~27,000) in 2018. The growth in the number of students starting undergraduate studies in CS is growing the fastest, growing 4-fold since 2006.

## PhD Specialization in AI

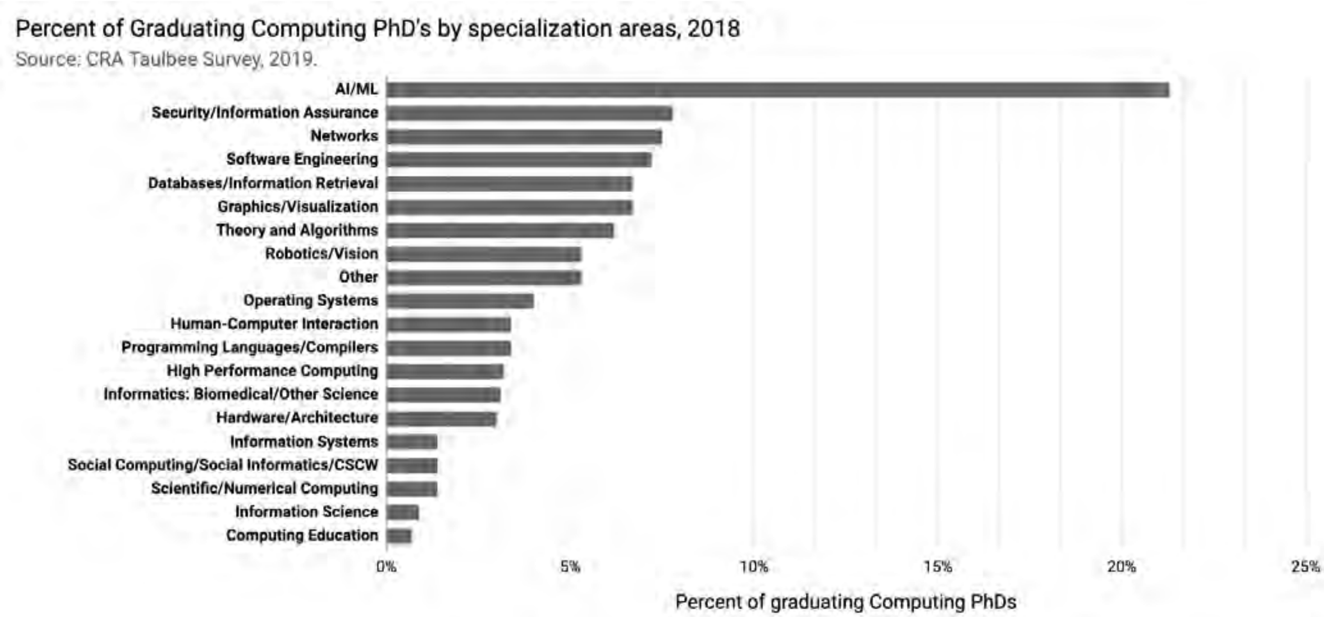



Fig. 5.6b.

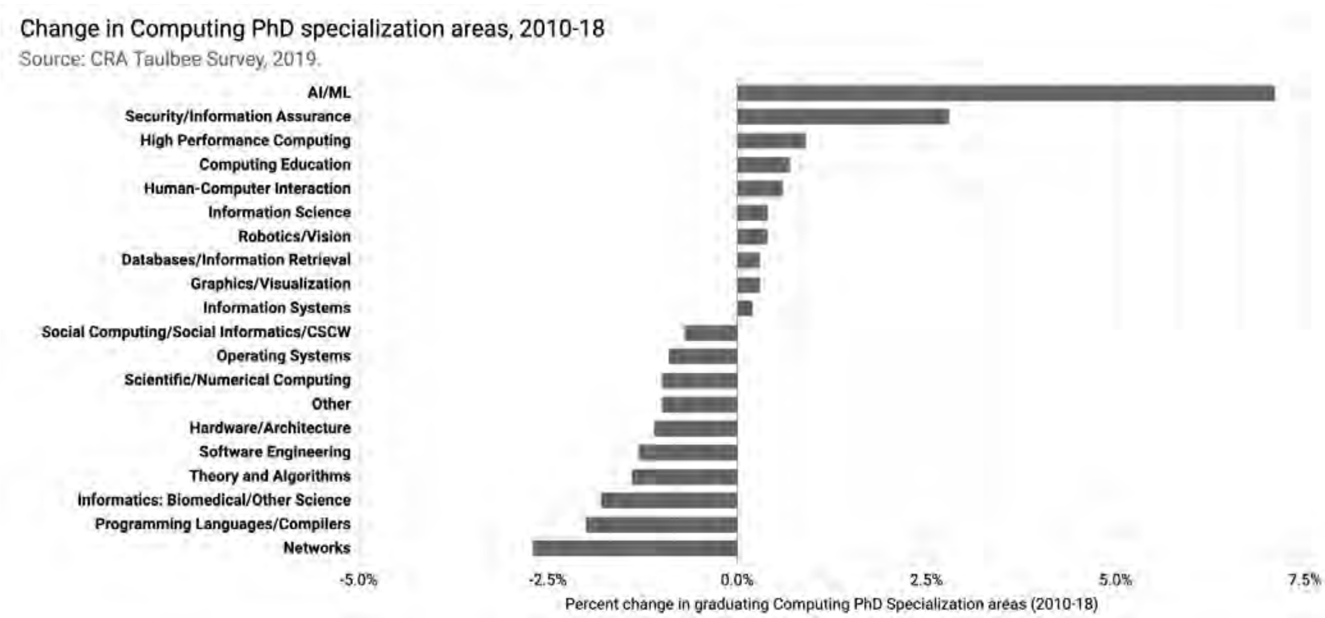



Fig. 5.6c.

## PhD to Industry

Over 150 new AI PhDs went to industry in 2018, and this number represents a percentage of new graduates three times as large as 2004 (Figures 5.7a & 5.7b). The percent of graduating AI PhDs going to industry increased from 21% in 2004 to over 62% in 2018. It should be noted that in many fields in academia there is no expectation that every PhD student goes on to get an academic job. For example, in the life and health sciences, the fields that award the most Ph.Ds, only 23% of PhDs held a tenured or tenure-track position in academia in 2017 (see Science, 2019).

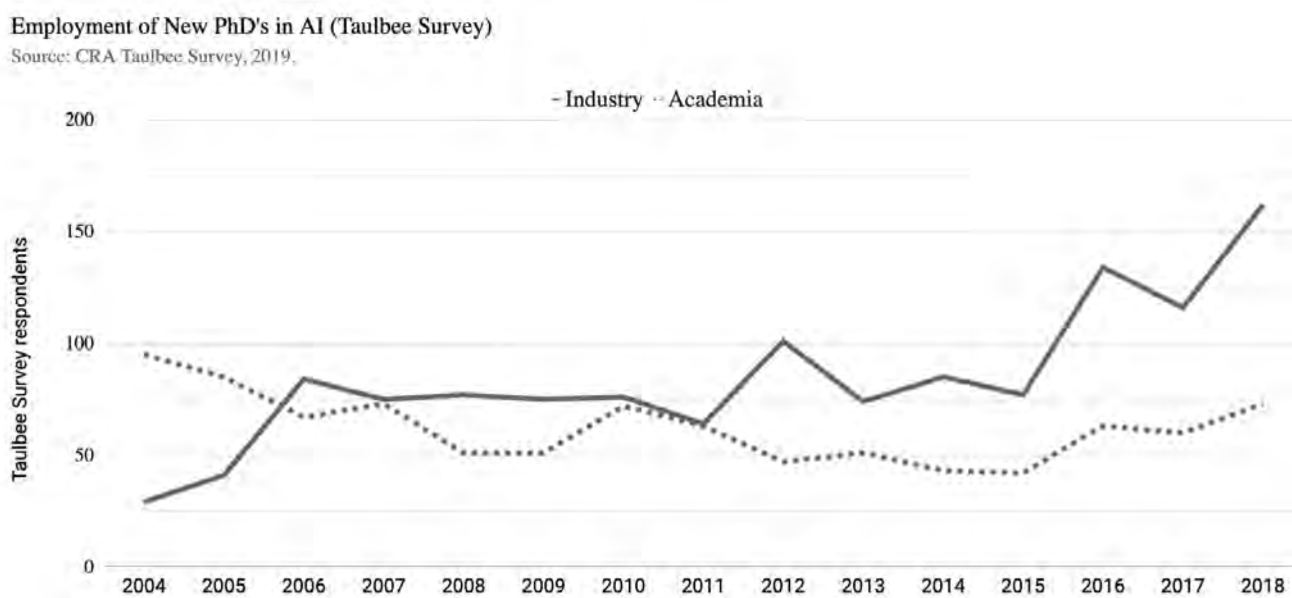



Fig. 5.7a.

Note: Categorization of specialty areas changed in 2008 and was clarified in 2016. 2004-7, AI and Robotics were grouped; 2008-present AI is separate; 2016 clarified to respondents that AI included ML.

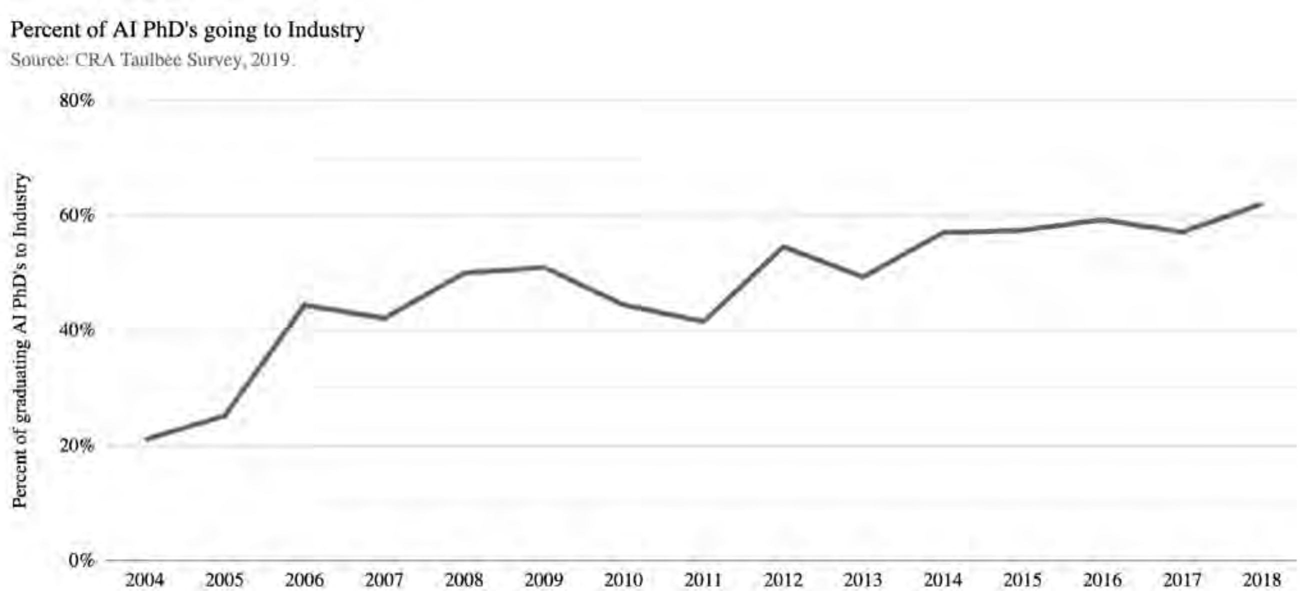



Fig. 5.7b.

## Faculty Hires

The trends in new faculty hires are presented next (Figures 5.8a, 5.8b & 5.8c). The 2018 Taulbee survey asked for the first time how many new faculty hires came from the following sources: new PhD, postdoc, industry, and other academic. 29% of new faculty hires came from another academic institution. Some may have been teaching or research faculty previously rather than tenure-track, and there is probably some movement between institutions. Thus, the total number hired overstates the total who are actually new to academia.[14]

The total number of CS tenure-track faculty has been rising steadily, making up half of the faculty hiring pool (Figure 5.8a). The percent of new female tenure-track faculty has remained largely constant at slightly over 21%. The percentage of new faculty who are international is smaller, at around 18% (Figure 5.8b). The last chart (Figure 5.8c) shows that although most new AI PhDs do a postdoc, the portion going directly tenure-track positions is increasing.

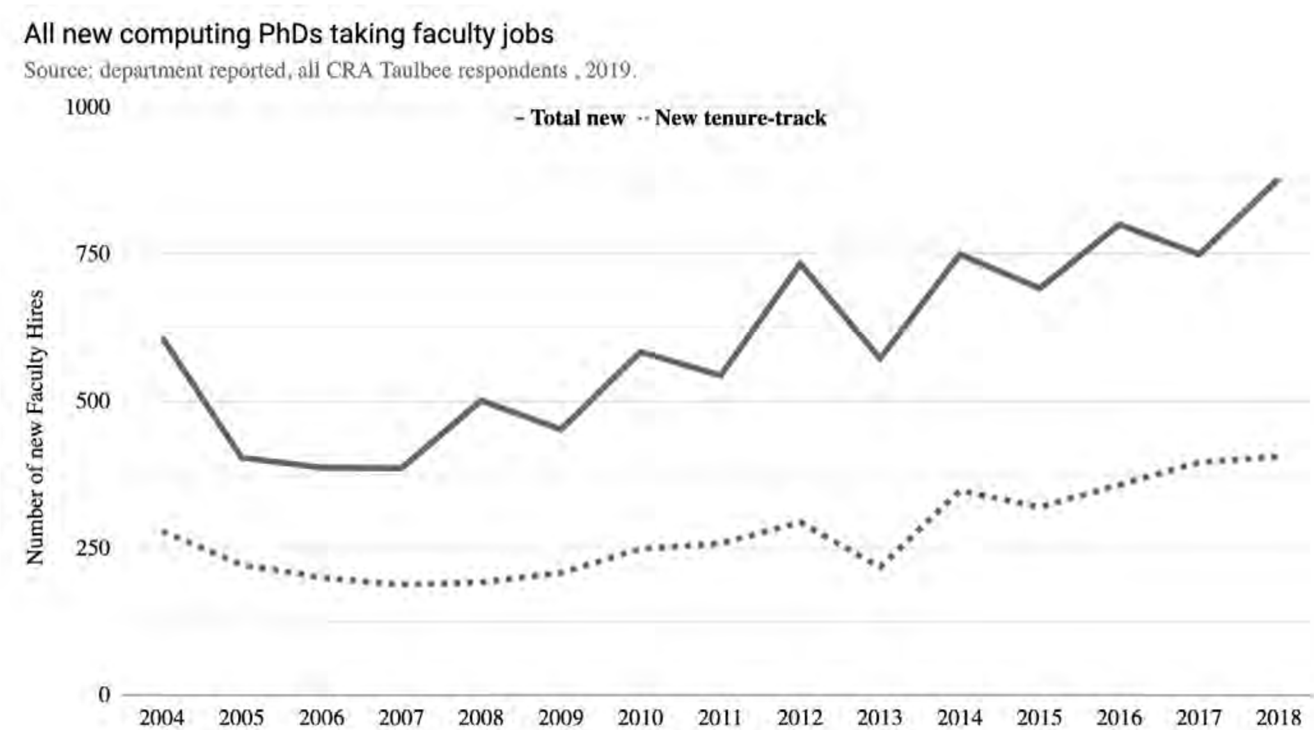



Fig. 5.8a.

[14] If Professor Q leaves institution A for Institution B, and A hires his replacement from Institution C, who hires a replacement from Institution D, who hires a new PhD, 4 institutions will report new hires but there's only a total increase of 1 new faculty member.

## AI Faculty Hiring

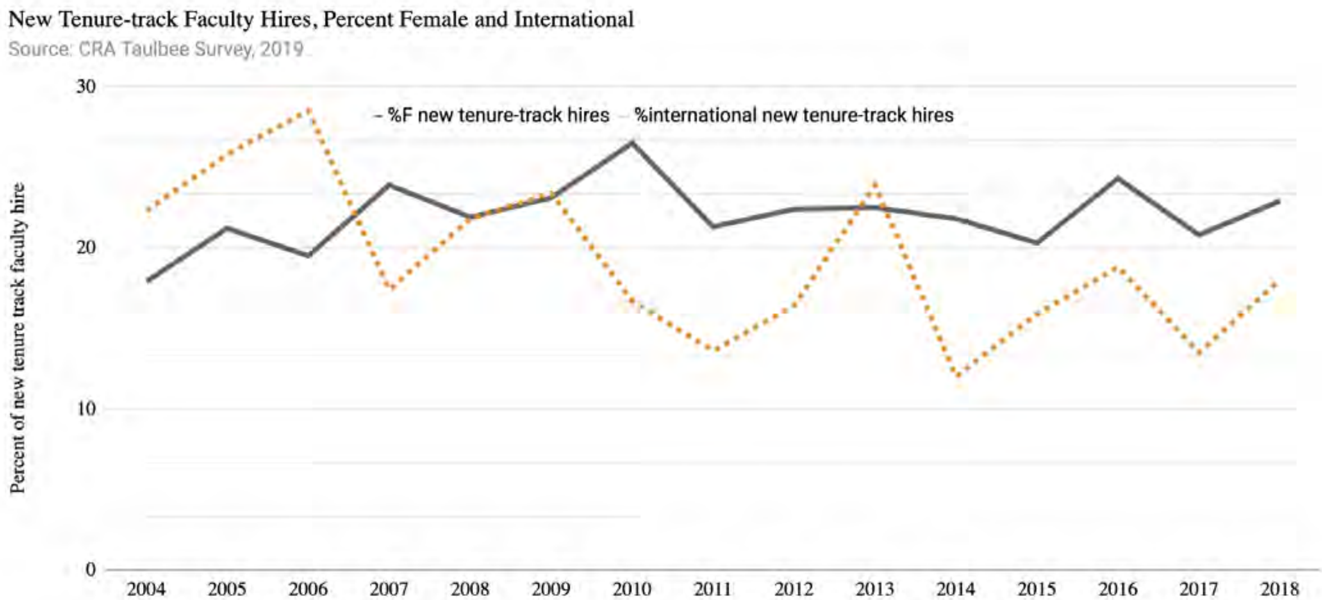



Fig. 5.8b.

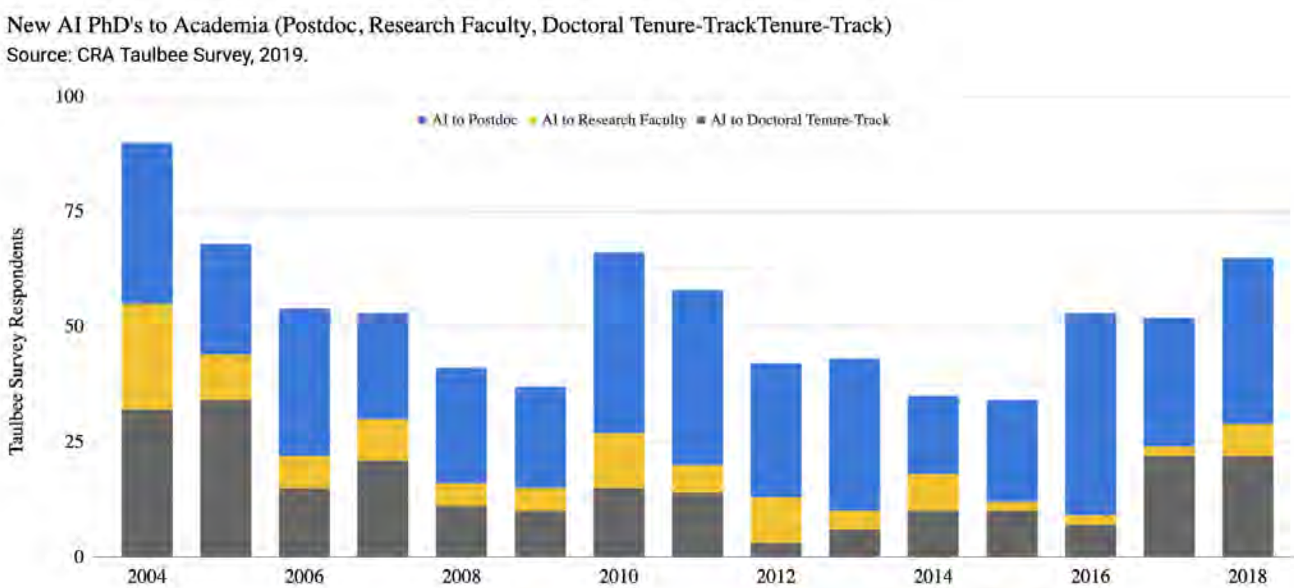



Fig. 5.8c.

## Faculty Departures

Goffman and Jin (2019) document the brain drain of AI faculty to industry.[15] The first graph (Figure 5.9a) below shows the number of North American tenure-track professors in AI leaving each year for an industry job. The movement affects both tenured and untenured faculty. This next figure (Figure 5.9b) shows the 18 North American universities with the largest losses of AI-related tenure-track or tenured professors between 2004 and 2018. Some of them left the university completely and some still keep university affiliations while working for companies. The three universities that lost the most AI faculty are Carnegie Mellon University (CMU), the University of Washington, and UC Berkeley. CMU lost 17 tenured faculty members and no untenured faculty, and the University of Washington lost 7 tenured and 4 assistant professors. For Canadian universities in the sample, the University of Toronto lost the most AI professors, 6 tenured faculty and 3 assistant professors.

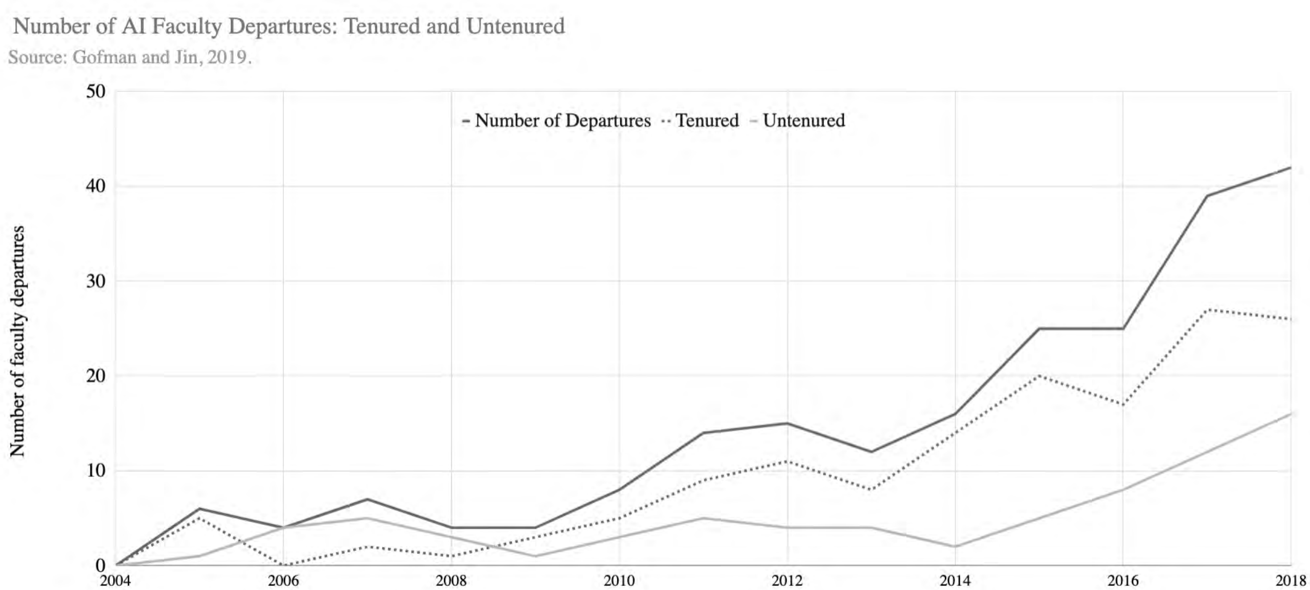



Fig. 5.9a.

*"AI's emergence as a general-purpose technology has resulted in an unprecedented brain drain of AI professors from academia to industry. What are the consequences of this brain drain is an important policy question."*
Michael Gofman, Assistant Professor of Finance, University of Rochester

[15] Gofman, M., and Z. Jin, (2019) "Artificial Intelligence, Human Capital, and Innovation", University of Rochester Working paper. This paper combines data from LinkedIn, CSRanking.com, CrunchBase, and Google Scholar. For AI professors leaving for an industry job is based on hand-collected sample from LinkedIn. The second method is to search in LinkedIn using reviewers' and program committee members' names of AI related conferences. Researchers also hand-collect data on faculty size at the top 100 universities' computer science departments from CSRankings.org, which provides the number of full-time, tenure-track and tenured CS faculty for each year based on data from DBLP Entrepreneurs'. Startups' information is based on a sample from the CrunchBase database Finally, hand-collected citation data from Google Scholar are used as a proxy for quality of research of AI faculty. Readers are referred for further technical details to the paper. The most updated AI brain drain index can be downloaded at http://www.aibraindrain.org

## Faculty Departures

The Gofman and Jin paper also documents trends in AI startups founded by graduates from North American universities. Figure 5.9c shows the North American universities that produced the most AI entrepreneurs who received their highest degrees from these universities from 2004 - 2018 and who established AI startups thereafter.[16] In the sample, 77 MIT graduates, 72 from Stanford and 39 from Carnegie Mellon University established AI startups. The Canadian university with the most AI entrepreneur alumni is the University of Waterloo, with 21 such graduates.

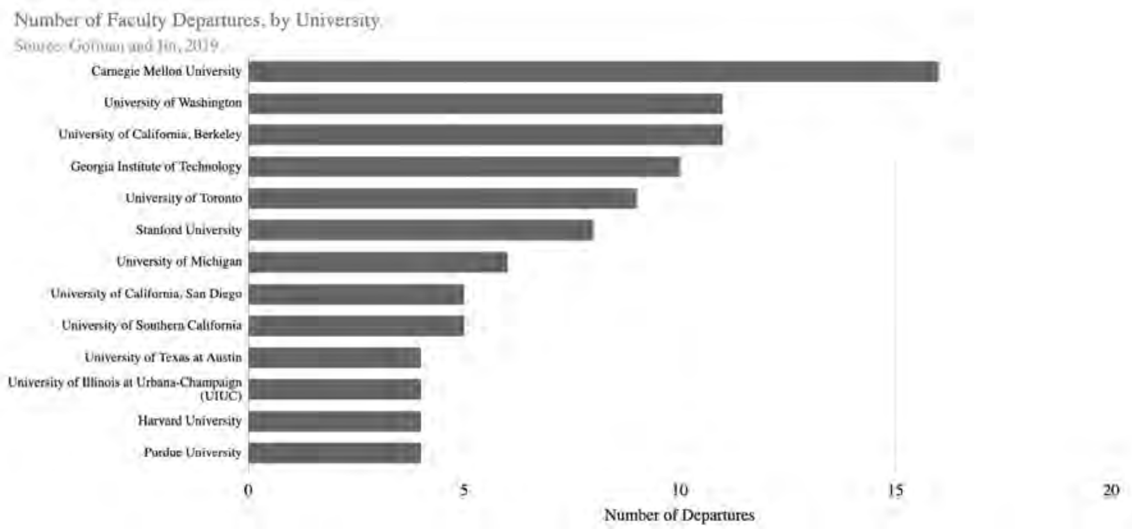



Fig. 5.9b.

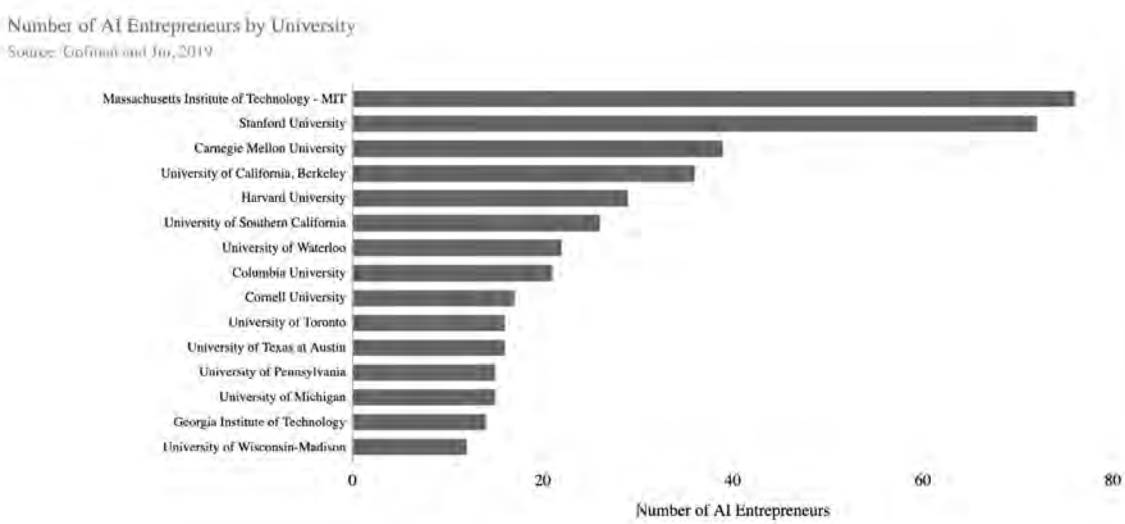



Fig. 5.9c.

*"AI startups require significantly more domain-specific knowledge than non-AI startups. AI brain drain negatively affects students' ability to gain the essential knowledge they need to be successful AI entrepreneurs."*
Zhao Jin, Finance PhD Candidate, University of Rochester

[16] An AI entrepreneur is identified if they start an AI startup after receiving their highest degree. AI startups are defined as startups that their business description includes one of the following fields: face recognition, neural networks, image processing, computer vision, semantic web, speech recognition, machine learning, natural language processing, artificial intelligence, deep learning, autonomous driving, autonomous vehicle, and robotics.

## Women in AI

Figure 5.10a plots the percent of female AI PhD recipients in the US between 2010-18, which has remained stable at around 20%. Figure 5.10b shows that in 2018, the percentage of new women faculty hire in computation fields is slightly higher than the proportion of female graduating with AI or CS PhD.

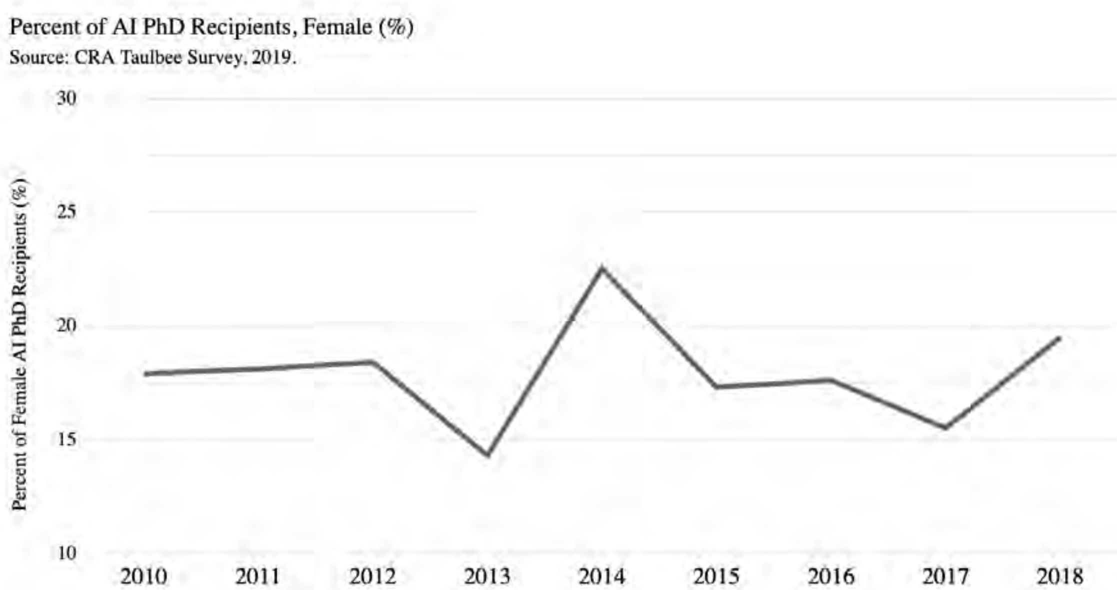



Fig. 5.10a.

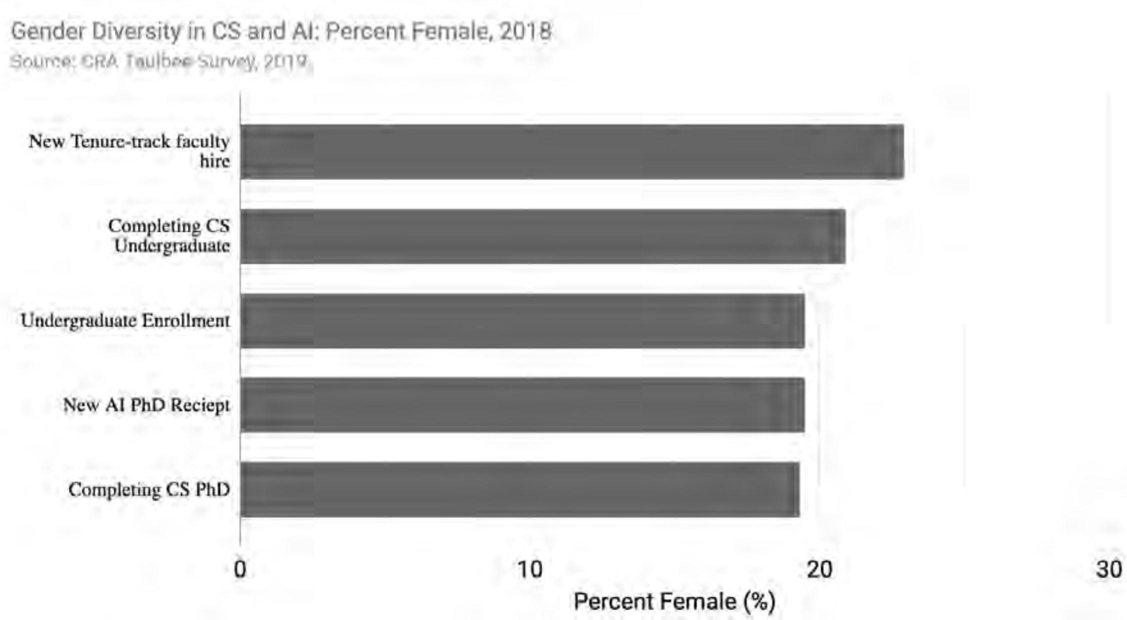



Fig. 5.10b.

**Between 2010 and 2018, the percent of female AI PhD recipients has remained stable at around 20%.**

[Education_Technical_Appendix]
[Access_Data]

## International Academic Presence

As shown in Figure 5.11a, the proportion of new AI PhD recipients from abroad has increased from below 40% in 2010 to over 60% in 2018. This remarkable trends indicates that the production of AI doctorates in the US is largely driven by international students.

Only a small portion of these graduates go to academia (around 18%) and an even smaller portion leave the US for jobs after graduating (around 10%) (Figure 5.11b).

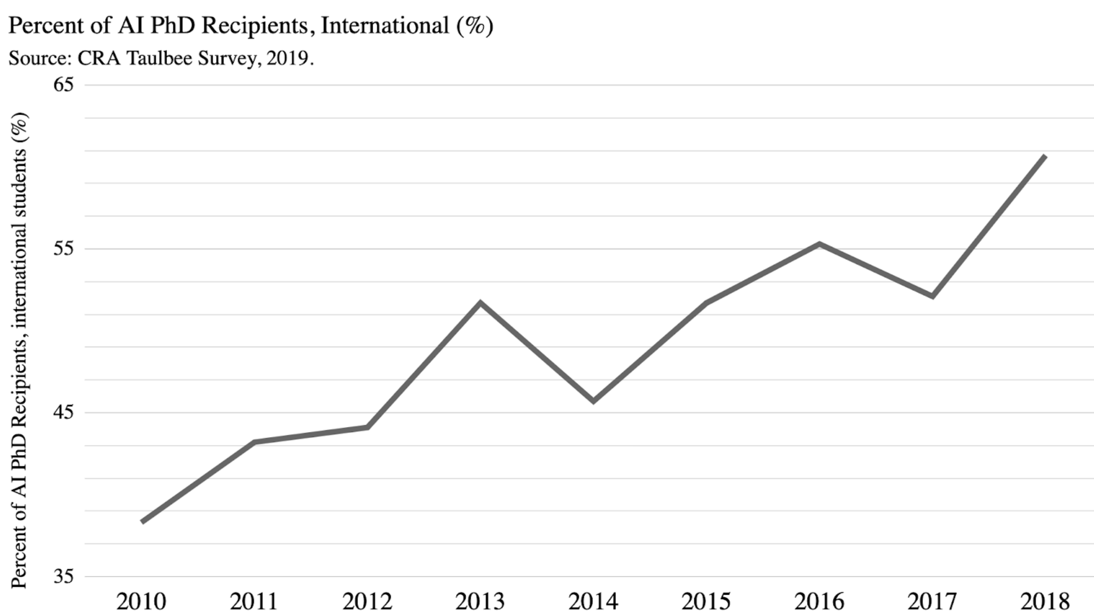



Fig. 5.11a.

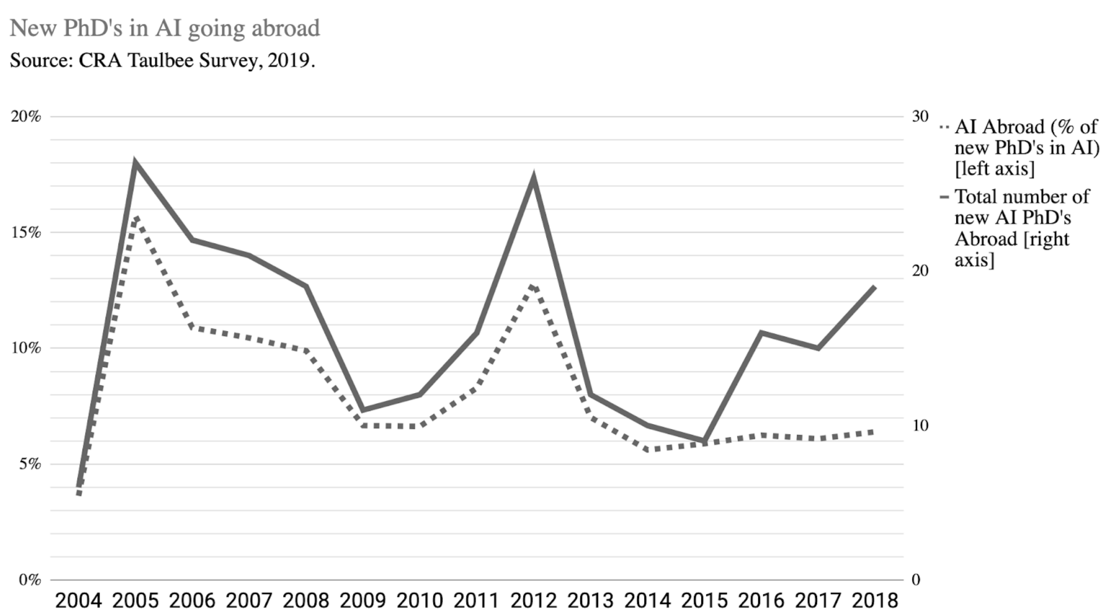



Fig. 5.11b.

**Between 2010 and 2018, the number of international doctoral recipients has increased from below 40% to over 60%.**

## Gender Diversity

The graph below (Figure 5.12) shows the gender breakdown of AI professors at several leading computer science universities around the world. Data was collected using faculty rosters on September 21, 2019.[17] Schools with easily accessible AI faculty rosters were selected. Due to the limited number of schools studied, these findings are a small view onto a much larger picture.

Across all educational institutions examined, males constituted the clear majority of AI department faculty, making up 80% of AI professors on average.

Within the institutions examined, ETH Zurich had the most female AI faculty as a percentage of the total department at 35%, while IIT Madras had the lowest percentage at 7%. There were no discernible differences in gender split across different regions of the globe, nor was there any correlation between the faculty gender split and department size.

There remains a  lack of data on diversity statistics in industry and in academia. See Appendix for data and methodology.

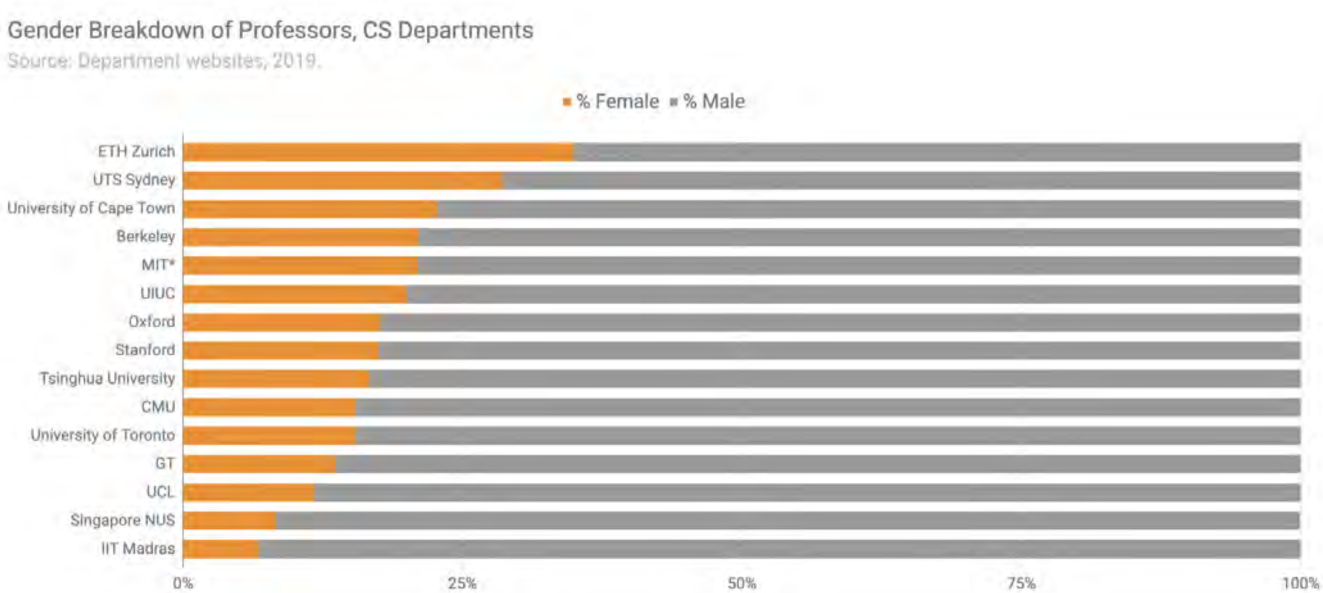



Fig. 5.12.

**A significant barrier to improving diversity is the lack of access to data on diversity statistics in industry and in academia.**

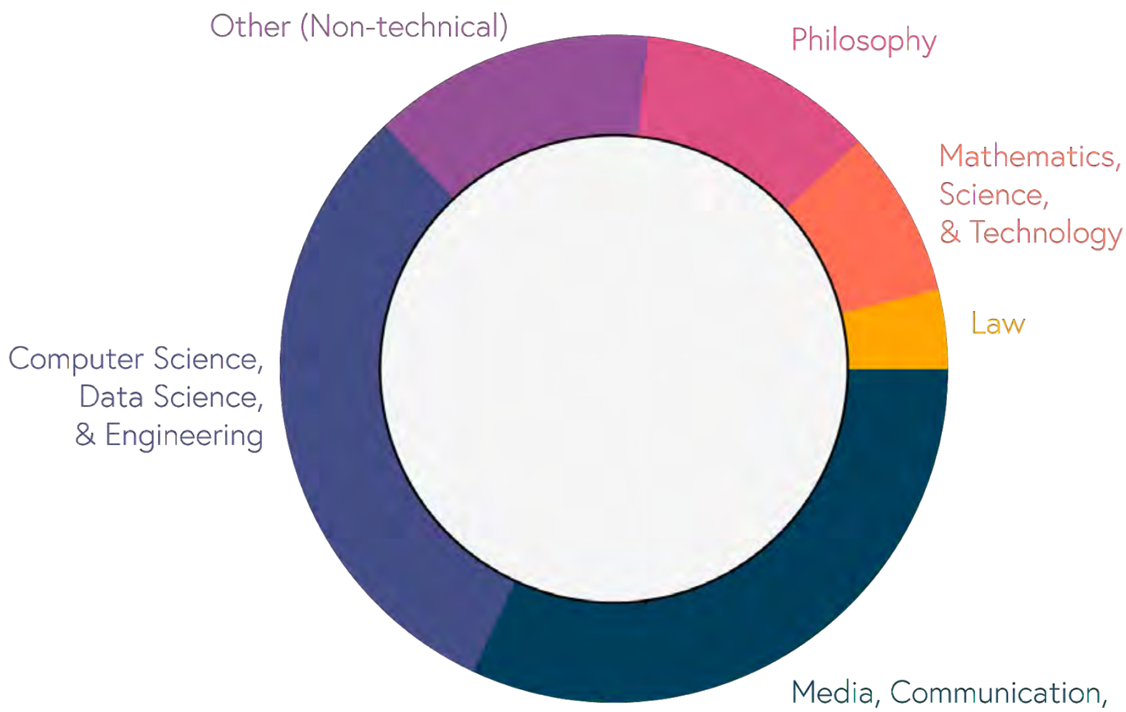
[17] "Female" and "male" are the terms used in the data. The Index aims to include options beyond binary in future data collection efforts.

## Ethics Courses

With the rise of AI, there has been an increased urgency to reimagine approaches to teaching ethics within computer science curricula. Currently, there are two approaches: (1) stand-alone ethics courses, which are individual courses that combine ethics and policy, and (2) program-wide efforts to integrate ethics into courses in the core computer science curriculum, like Harvard's Embedded EthiCS and other efforts in the Responsible CS Challenge. Fiesler et al., 2019 and Grosz et al., 2019 discuss these models.[18] (Figures 5.13).[19] The first approach includes broad "CS and Ethics" courses, like Stanford's CS181 and Berkeley's CS 195, which include AI topics, and more specific "AI and Ethics" courses, like Harvard's CS 108 and Cornell's CS 4732, which typically examine ethical challenges from several different areas of AI. The second approach adds ethics modules to the full range of individual AI and ML courses (as well as to courses in other areas of CS). Both approaches are important, and some universities are working to integrate both.

**Tech Ethics Courses, by Department**

Sample includes 235 courses from universities around the world.




Source: Tech Ethics Curriculum (Casey Fiesler), 2019

Fig. 5.13a.

*"In addition to encouraging contribution to this growing research space, we also hope that this work can serve as a call to action that can encourage and assist instructors at all educational levels who are interested in including ethics as part of their class, as well as computing programs with a goal towards increasing the reach of ethics across a curriculum."*
Casey Fiesler, Natalie Garrett, Nathan Beard
What Do We Teach When We Teach Tech Ethics? A Syllabi Analysis

[18] B.J. Grosz, D.G. Grant, K.A. Vredenburgh, J. Behrends, L. Hu, A. Simmons, and J. Waldo, (2019) "Embedded EthiCS: Integrating ethics broadly across computer science education." Communications of the ACM.
[19] The dataset downloaded from the Tech Ethics Curriculum spreadsheet had 238 courses listed. At the time of analysis 235 courses had the department listed. Included are what the instructor (or crowdsourced additions) would have deemed appropriate to add to a list of "tech ethics courses". In this dataset, the authors did not make any judgments about the character of the course beyond its inclusion in the crowdsourced list. It should be noted that by no means this analysis is a representative sample.

[Tech_Ethics_Curricula]
[Access_Data]

## Measurement Questions

- A common definition of AI skills is required to assess AI education outcomes in a comprehensive manner.
- Likewise, there needs to be a survey (either annual or real-time) to accurately estimate AI course enrollment and graduation for undergraduate, masters, and PhD programs that are nationally representative and comparable across countries and regions.
- Innovative methods to scrape web data of university courses and programs could also be an invaluable resource for tracking AI learning. It is also important to get a sense of the generation of AI-trained workforce, in the US and globally.

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# Chapter 6: Autonomous Systems

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[Autonomous_Systems_Technical_Appendix]

## Introduction

AI is a key component of Autonomous Systems. This chapter presents data on Autonomous Systems divided in two sections: Autonomous Vehicles (AV's) and Autonomous Weapons (AW's). The AV section shows the countries (AI Index web survey) and cities (Bloomberg Philanthropies) testing AV's. This is followed by US state policy on AV from the National Conference on State Legislation (NCSL). Data from the State of California presents metrics on total AV miles driven and number of companies testing based on the Department of Motor Vehicles (DMV) Disengagement Reports. The results from DMV Collision reports are also analyzed to present safety and reliability metrics related to AVs. The section on AW presents the known types of autonomous weapon deployments and by which country based on expert survey data collected by the Stockholm International Peace Research Institute (SIPRI).

## Global

Autonomous Vehicles (AVs) are one of the most visible and potentially disruptive applications of AI. There are prototypes currently being tested around the world. While it is difficult to present a fully comprehensive list of countries where testing is taking place, data from Bloomberg Philanthropy offers insight on the global reach of AV's beyond the United States. The map (Figure 6.1a) below shows at least 25 countries with cities that are testing AV's.

Nordic countries and the Netherlands have made big strides in deploying electric vehicles (EV) charging stations and in using AV's for logistic supply chain management. In cooperation with Germany and Belgium, AV truck platoons will run from Amsterdam to Antwerp and Rotterdam to the Ruhr Valley. Similarly, Singapore has designated test areas in the metropolis for AV's (Figure 6.1b).

**World Map of Countries Testing AVs**

Source: Online searches on nations testing AV's.

Fig. 6.1a.

**Cities Testing Autonomous Vehicles**

Source: Bloomberg PhilanthropiesBloomberg Philanthropy, 2019.

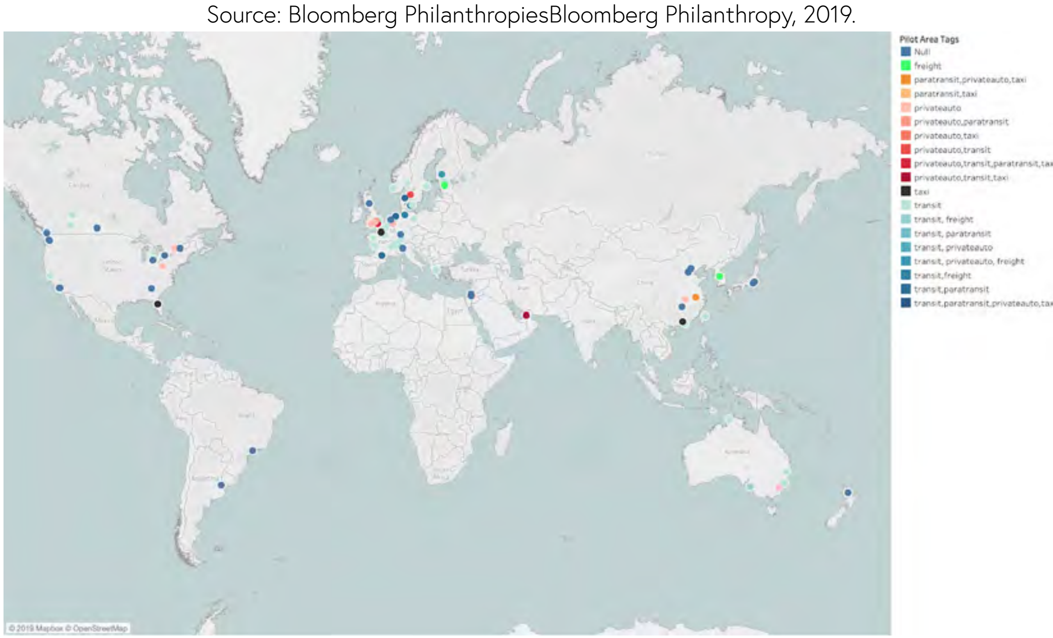


Fig. 6.1b.

## US: State Policies for AVs

California was the first state with autonomous vehicle testing regulations. The number of states considering legislation related to autonomous vehicles has been increasing (Figure 6.2). Since 2012, at least 41 states and D.C. have considered legislation related to autonomous vehicles.[21] Ten states authorize full deployment without human operator, including Nevada, Arizona, or Texas, as well as many States on the east coast. Colorado authorized full deployment with a human operator. Many states, such as South Carolina, Kentucky, and Mississippi, already regulate truck platooning.[22]

**US State Law on AVs**

Source: National Council on State Legislation (NCSL), Governors Highway Safety Association (GHSA), 2019.

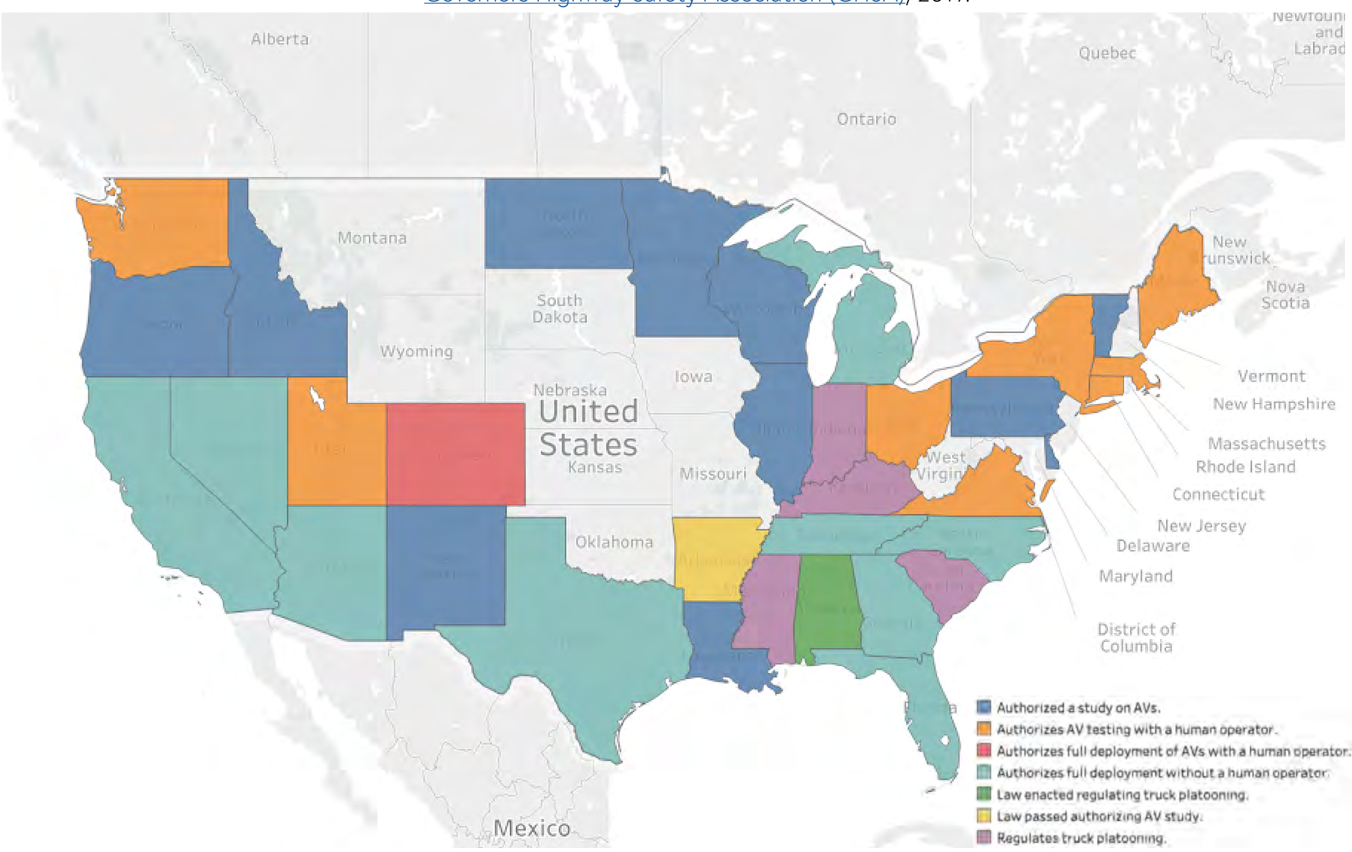


Fig. 6.2.

[21]In 2012, six states, in 2013 nine states and D.C., in 2014 12 states, in 2015 16 states, in 2016 20 states, in 2017 33 states enacted AV related bills. In 2018, 15 states enacted 18 AV related bills. In 2017, 33 states have introduced legislation. In 2016, 20 states introduced legislation. Sixteen states introduced legislation in 2015, up from 12 states in 2014, nine states and D.C. in 2013, and six states in 2012. In total, 29 states have enacted legislation related to autonomous vehicles. Readers can find California DMV Title 13, Division 1, Chapter 1, Article 3.7 –Testing of Autonomous Vehicles which defines the capability and operations that meets the definition of Levels 3, 4, or 5 of the SAE International's Taxonomy and Definitions for Terms Related to Driving Automation Systems.

[22]Truck platooning is the linking of two or more trucks in convoy, using connectivity technology and automated driving support systems. These vehicles automatically maintain a set, close distance between each other when they are connected for certain parts of a journey, for instance on motorways (ACEA, 2019). Multi-brand platooning (up to SAE level 2) with the driver still ready to intervene. By 2023, it should be possible to drive across Europe on motorways (thus crossing national borders) with multi-brand platoons, without needing any specific exemptions. Subsequently, allowing the driver of a trailing truck to rest might come under consideration. Full autonomous trucks will only come later. On 09/2016, NHTSA issued a "Federal Policy for safe testing and deployment of automated vehicles" .

## California

In 2018, the State of California licensed testing for over 50 companies and more than 500 AVs, which drove over 2 million miles.[23] Figure 6.3 below shows the number of companies that are testing AV's in California (blue line on the left axis) and the total number of AVs on the road (red line on the right axis). Both metrics grew at an annual compounded growth rate (2015-18) around 90%, increasing sevenfold since 2015. The second chart (Figure 6.4) shows the total number of miles driven and total number of companies testing autonomous vehicles (AVs). This number is calculated by summing the total number of miles driven by individual AV companies, as reported in the Annual DMV Disengagement Reports. 2018 was the year of fastest growth in total miles covered by AVs totaling over 2 million miles. The compounded annual growth (2015-18) for total AV miles driven was 64% growing fourfold since 2015.

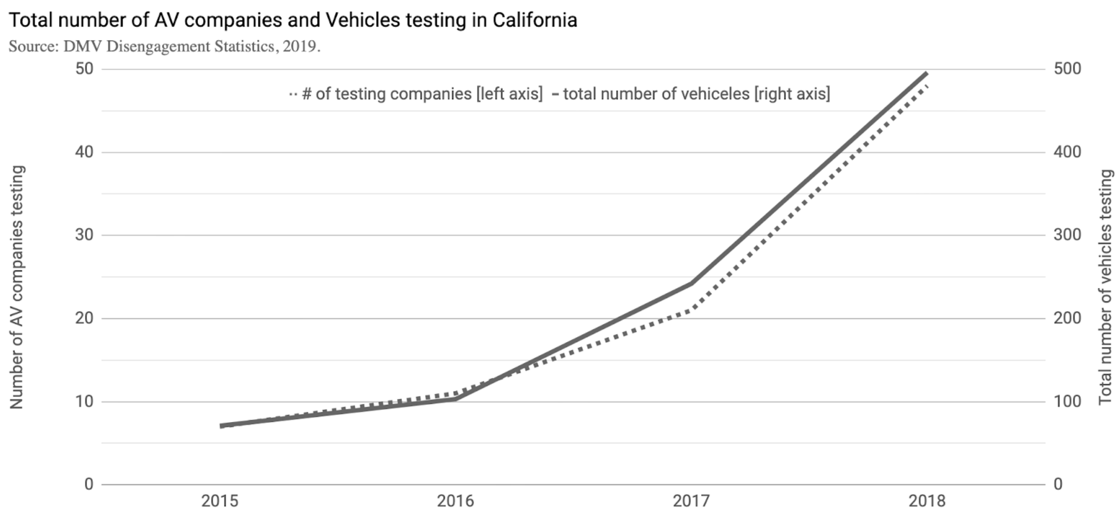


Fig. 6.3.

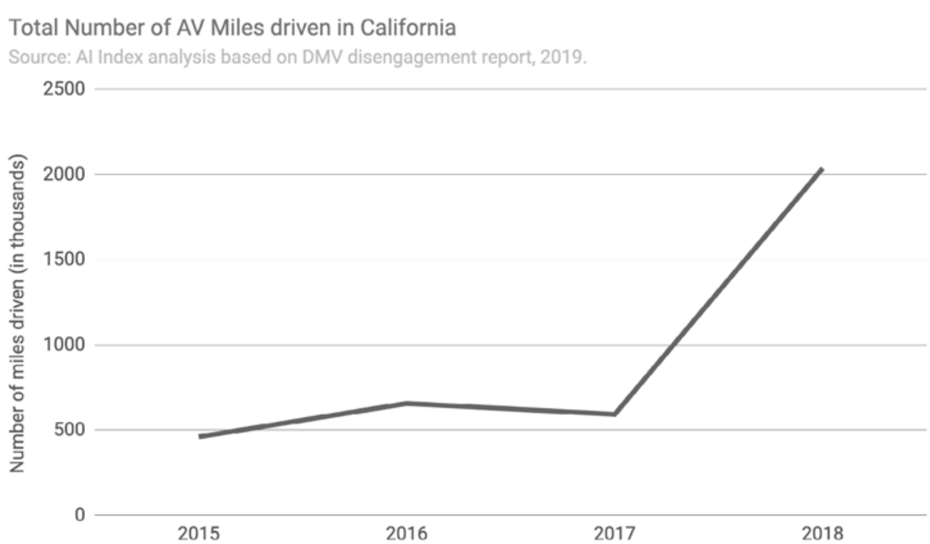


Fig. 6.4.

[23]Effective on September 16, 2014, the autonomous vehicles testing regulations in California require a driver and every autonomous mile, accident, and disengagement to be reported under CA regulation §227.02.

## Safety and Reliability

Six times more people have died in traffic related fatalities than the number of fatalities in all wars for the US (Washington Post, 2019). The hope is that AVs can help reduce traffic fatalities in both advanced and developing countries.

Crashes per million miles driven in autonomous mode is the simplest and is the most reliable measure of AV safety (Figure 6.5). In 2018, AV's in CA had 46 crashes coded as being in the autonomous mode in 2018, while driving 2.05 million miles* in the autonomous mode. Or 22.44 crashes per million miles driven. To put this number in perspective below is a table from a 2016 UMTRI report that took an early look at CA AV crash rates. Even adjusting for under-reporting, the 22.44 crashes per million miles for the CA AV fleet is about 5.5x higher than the ADJUSTED rate expected for human-driven vehicles. (see notes on crash rate in Appendix).

In the early stages of development of AV testing, the number of AV related fatalities could be higher than normal traffic fatalities. A higher crash rate may be observed through every mode of automated driving. For example, in 2018 California had 2.05 million AV miles. The point estimate of human driver is at 4.1 (UMTRI) the expected crashes for AV is 8.4 with actual AV crashes in California of 46.

The pie charts summarize the Collision Report of the DMV. In most of the accidents, a car driven in the daytime by a human rear ends an AV that is either stopped or going straight. Studies suggest that these are caused by unexpected behavior by the AV or error by the human driver. Most damages have been minor.

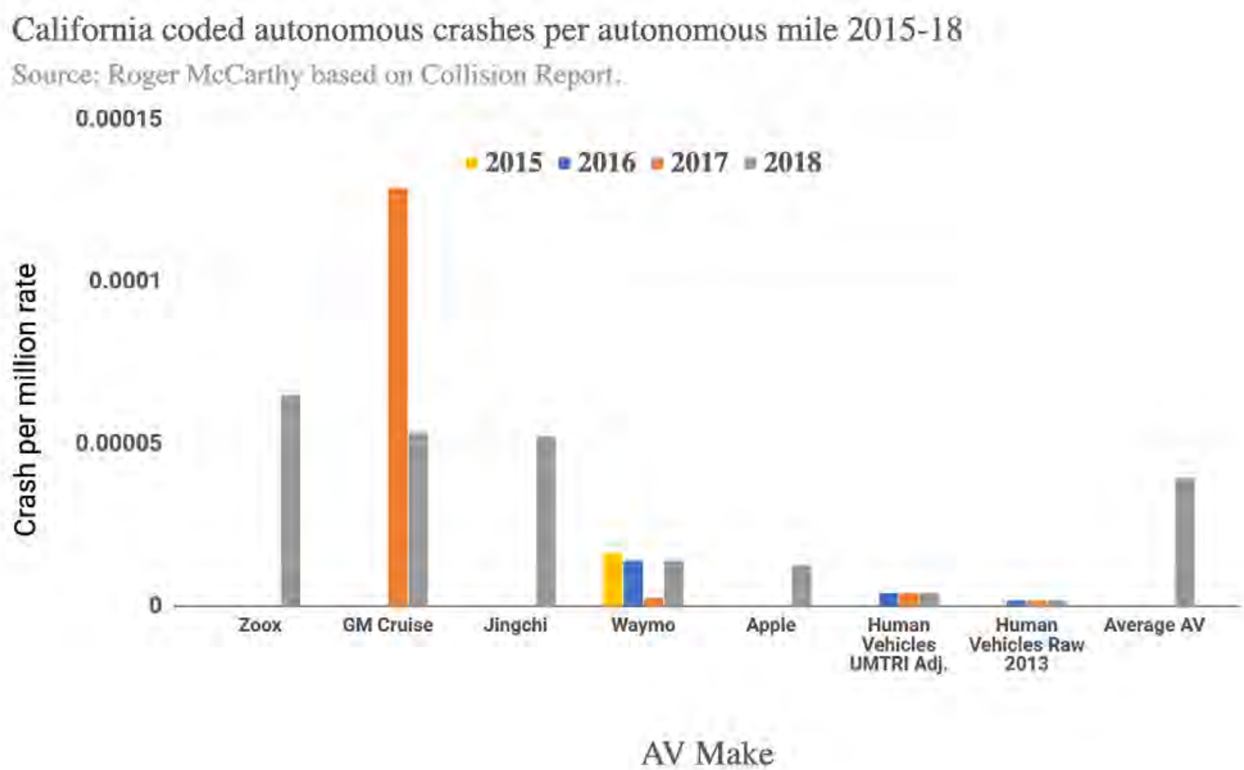


Fig. 6.5.

*"I believe the 2018 AV crash rate is an underestimate of the true crash rate, and I expect the AV crash rate to continue rising. The calculated 22.4 2018 crash rate is based on the OL 316 crash form coding, which doesn't capture the effect of the AV driver turning off the AV mode moments before a crash. I believe more accurate coding would move additional crashes into the "autonomous" category. Secondly, AV's are driven, and have their crashes, under virtually ideal daytime driving conditions. When AV's are finally tested in more adverse environments of rain, snow, and fog, I am sure the AV crash performance will degrade, as with human drivers. The technical challenges of keeping sensors clean and operational under such conditions remain."*
Roger McCarthy, Principal, McCarthy Engineering

## Safety and Reliability

**Summary of Collision Report for Autonomous Vehicles in California, 2018**

Source: DMV Collision Reports, 2019.


Fig. 6.6.

## Measurement Questions

- The data uncertainties related to disengagement reports are well-known. Improvement in fine-grained data collection and intrinsic reporting from AV companies is critical, as is understanding which are the identifiable AI components in AV systems. The failure and incidents report of AV-AI components is industry sensitive information, which nevertheless requires standardized measurement, reporting, and identification of reliability metrics. In particular, diverse approaches to reporting even when using the same measure (for example, disengagement) highlights challenges in standardization. Further, measurement practices from companies could be associated with self-selection bias that accentuate the positive and share selectively (voluntary safety self assessment).

- Risk-informed performance-based approaches could characterize all uncertainties including engineering ones into the operation, policy and regulation of AVs. Adoption of probabilistic risk analysis from other complex engineering domains could help empower innovation and lead to better design, adequate safety features and sound policy (see Summary and Presentation Slides from: Workshop on Risk Analysis for Autonomous Vehicles: Issues and Future Directions).

## Autonomous Weapons

Autonomous Weapons (AW) include various systems for either defensive or offensive capabilities. For example, Automated Target Recognition (ATR) systems autonomously acquire targets and have been in existence since the 1970s. Existing systems are largely defensive in nature with humans determining the decisions surrounding the time, location, and category of targets. A recent survey found that at least 89 countries have automatic air defense systems in their arsenal and 63 countries deployed more than one type of air defense system. Active Protection (AP) systems are developed and manufactured by only nine known producing countries. The charts below show the total known number of AW systems known to be deployed globally according to expert-curated data from the Stockholm International Peace Research Institute (SIPRI) (Figure 6.7a). The total number are classified into three labels: combative for military purpose with more than targeting capabilities i.e. machine makes the execution decision, systems with targeting capabilities only, and systems designed for intelligence, reconnaissance, and surveillance purposes including logistics, EODs, etc.. called others. A SIPRI report on [Mapping the Development of Autonomy in Weapon Systems] provides a detailed survey of AW systems. The total number of known AW systems by countries is presented between 1950-2017 (Figure 6.7b).

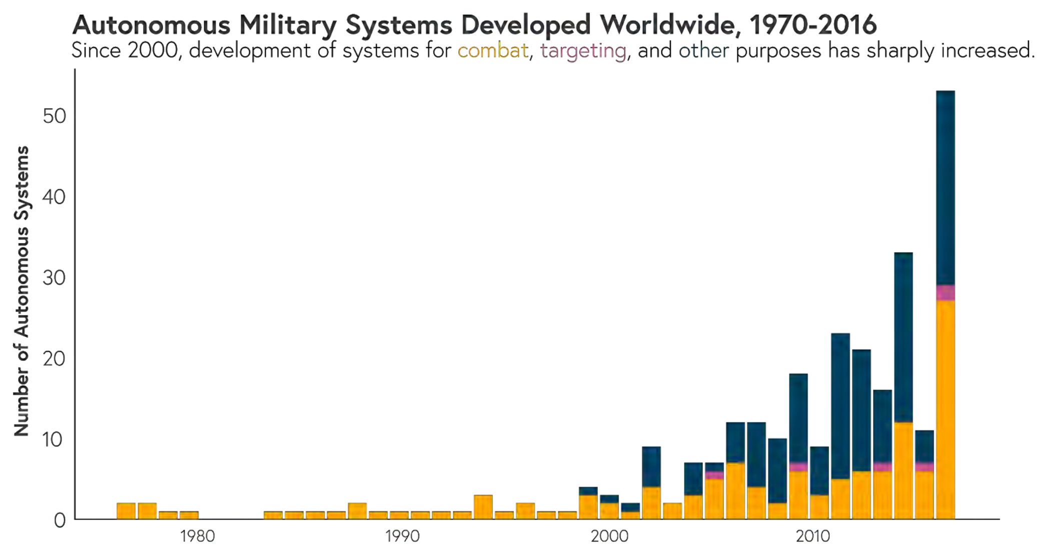


Fig. 6.7a.

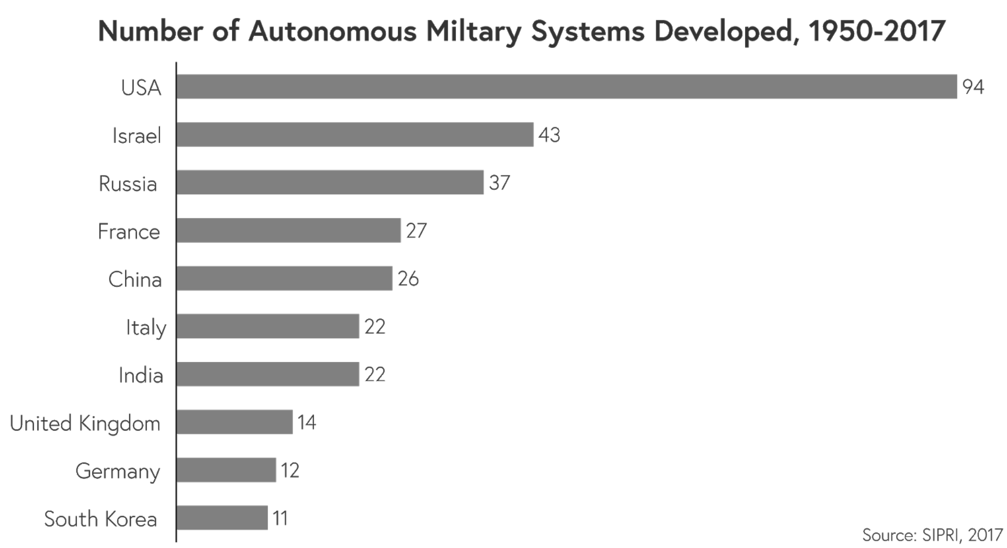


Fig. 6.7b.

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# Chapter 7: Public Perception

## Central Banks

Central banks around the world demonstrate a keen interest in AI, especially for its ability to predict geopolitical and macroeconomic conditions, and better understand the regulatory and policy environment. The first chart below plots the global aggregate document types by central banks across 14 central banks (Figure 7.1a).[24] It shows a significant increase in central bank communications mentioning AI, with a shift from other publications to speeches mentioning AI over time. This more intensive communication reflects greater efforts to understand AI and the regulatory environment as it relates to the macroeconomic environment and financial services. The second chart plots the ranking of central banks based on the total number of AI mentions for the last ten years (Figure 7.1b). The Bank of England, the Bank of Japan, and the Federal Reserve have mentioned AI the most in their communication.

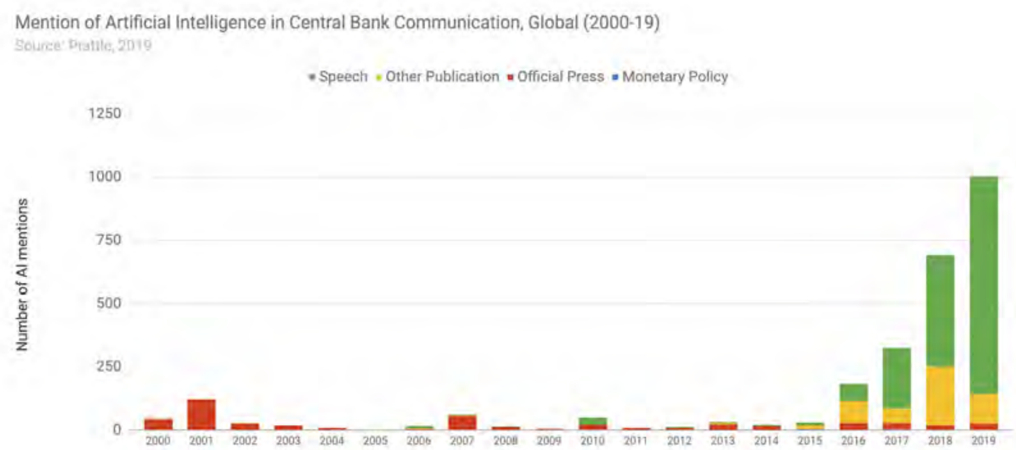


Fig. 7.1a.

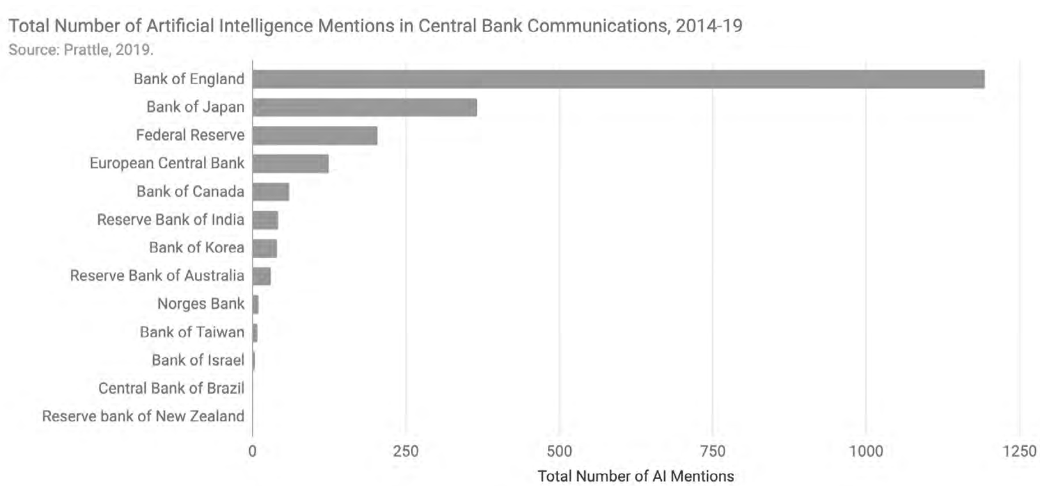


Fig. 7.1b.
Note: The chart represents data with latest data point till Q12019.

*"In the last few years, the Bank of England has pursued a clear research agenda around AI as well as the use of blockchain and cryptocurrencies. Other central banks, like the Fed and BOJ, have addressed these topics in speeches, but they are just beginning to structure formal research agendas around AI."*
Evan Schnidman, founder and CEO of Prattle

[24] Bank of Canada, Bank of England, Bank of Israel, Bank of Japan, Bank of Korea, Bank of Taiwan, Central Bank of Brazil, European Central Bank, Federal Reserve, Norges Bank, Reserve Bank of Australia, Reserve Bank of India, Reserve Bank of New Zealand, Sveriges Riksbank.

## US Government Perception

Government officials are paying more attention to AI. The Index partnered with Bloomberg Government to analyze mentions of AI in the US congress. Each data point on the graph refers to one piece of proposed legislation, one report published by a congressional committee, or one report published by the Congressional Research Service (CRS), which serves as a nonpartisan fact-finding organization for US lawmakers, that explicitly references one or more AI-specific keywords. The data shows a greater than ten-fold increase in activity around AI in the 2017-2018 Congress, compared to prior years. More activity can be expected: our preliminary data for the 2019-2020 congress shows a further increase in activity when compared to prior years. With more than a year remaining in its term, the 116th will undoubtedly become the most AI-focused US Congress in history.

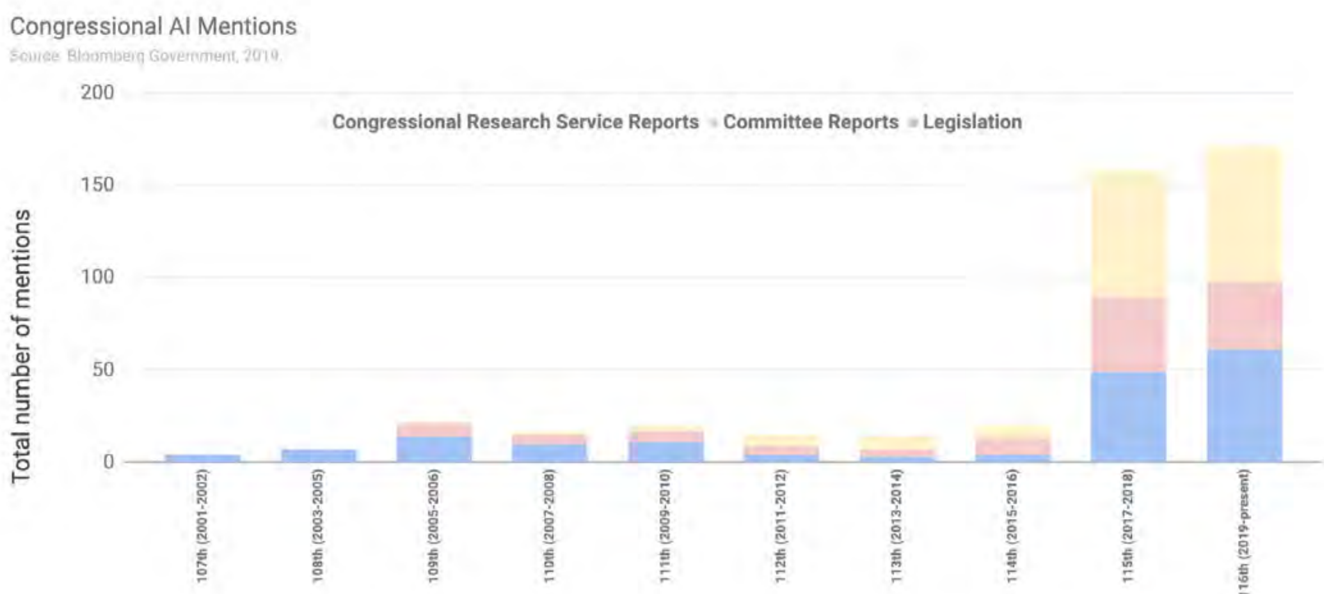


Fig. 7.2.

## US, Canada, and the UK Government Perception

The next graphs show mentions of the terms 'Artificial Intelligence' and 'Machine Learning' in transcripts of US Congress (Figure 7.3a), the records of proceedings (known as Hansards) of the Parliaments of Canada (Figure 7.3b) and the United Kingdom (Figure 7.3c). Prior to 2016, there were few mentions of artificial intelligence or machine learning in the parliamentary proceedings of each country. Mentions appeared to peak in 2018, and, while remaining significant, have declined in 2019 for Canada and the United Kingdom. In transcripts of the US Congress, 2019 was year of highest AI mentions to date.

Note that it is difficult to make country-to-country comparisons, due to variations in how remarks and comments are counted between each (see Appendix for methodology). Thus, rather than country-to-country comparisons, it would be better to compare trends over time within a country.

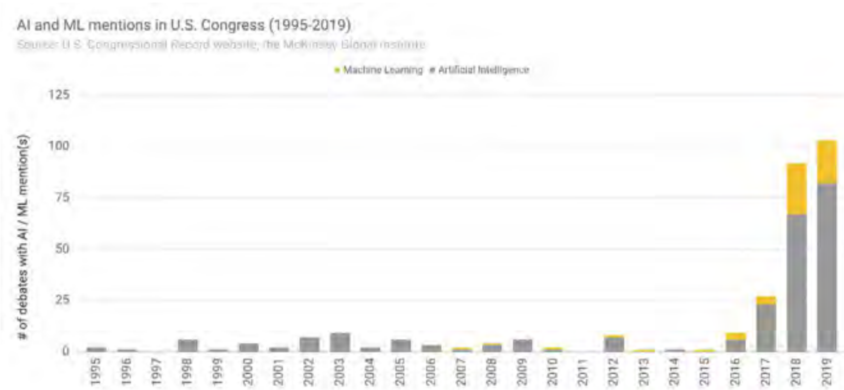


Fig. 7.3a.

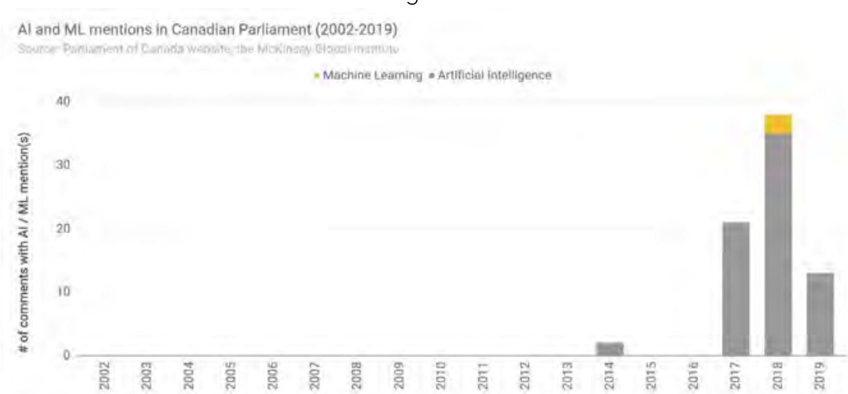


Fig. 7.3b.

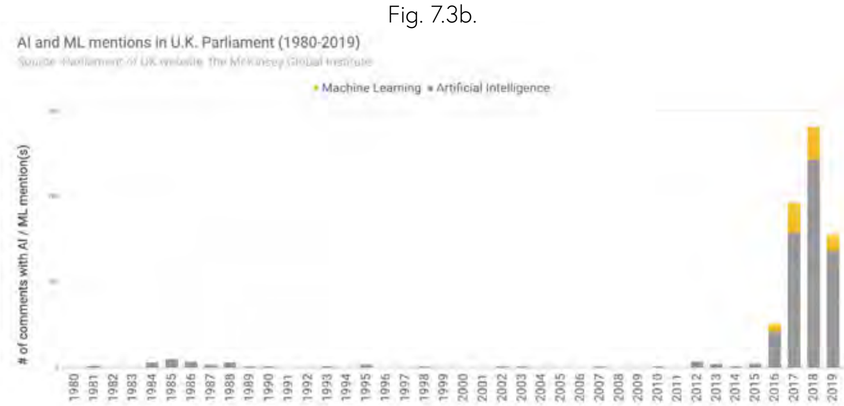


Fig. 7.3c.

## Corporate Perception

The following earnings calls data includes all 3000 publicly-traded companies in the US, including American Depositary Receipts (ADRs - foreign-listed companies that also trade on a US exchange). The charts below show the individual instances of AI-related terms mentioned on earnings calls (Figure 7.4a). The share of earning calls where AI is mentioned has increased substantially, from 0.01% of total earnings calls in 2010 to 0.42% in 2018.

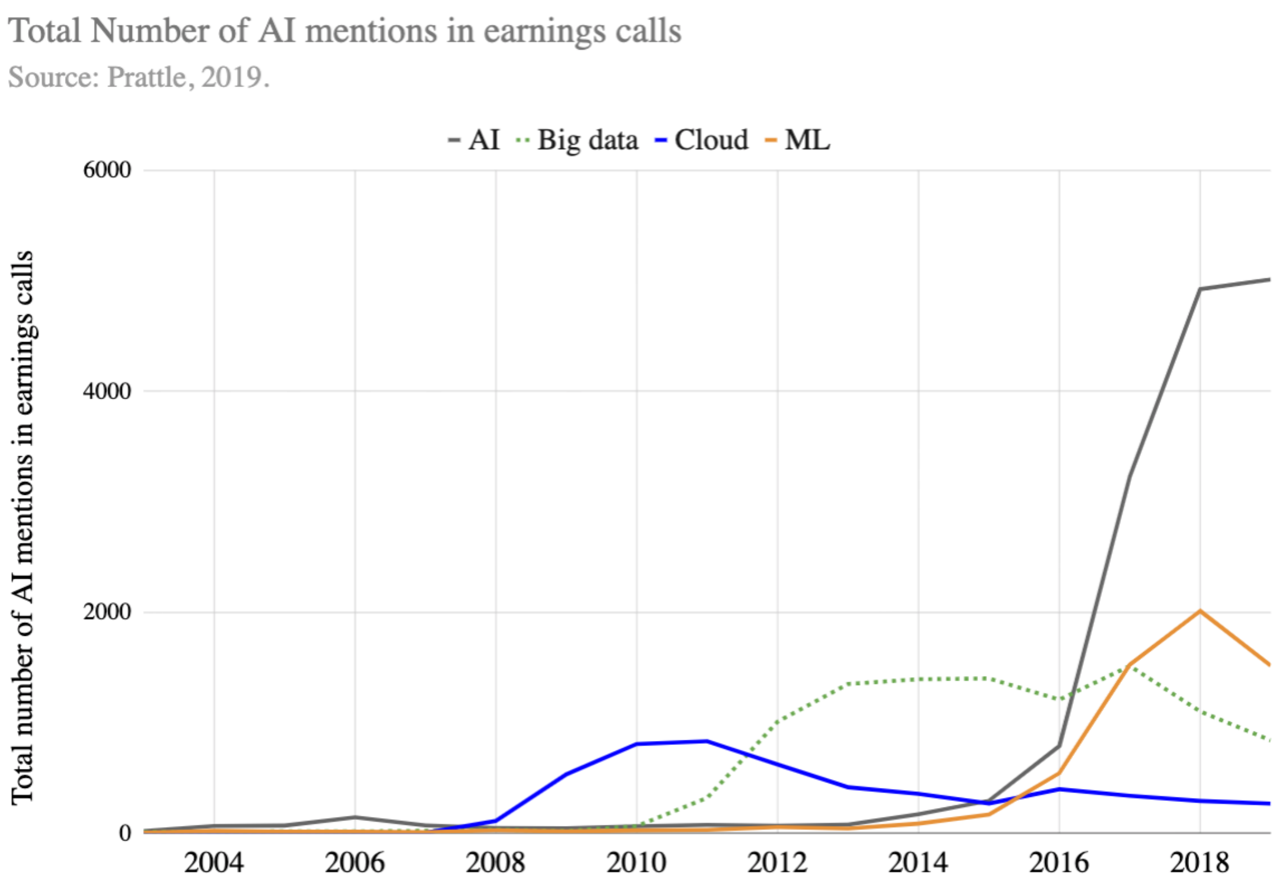

Fig. 7.4a.

## Corporate Perception

Among sectors, finance has the largest number of AI mentions in earnings calls from 2018 to Q1 of 2019, followed by the electronic technology, producer manufacturing, healthcare technology, and technology services sectors (Figure 7.4b). A normalized view for the mentions of AI relative to total earnings calls is presented in the Appendix chart.

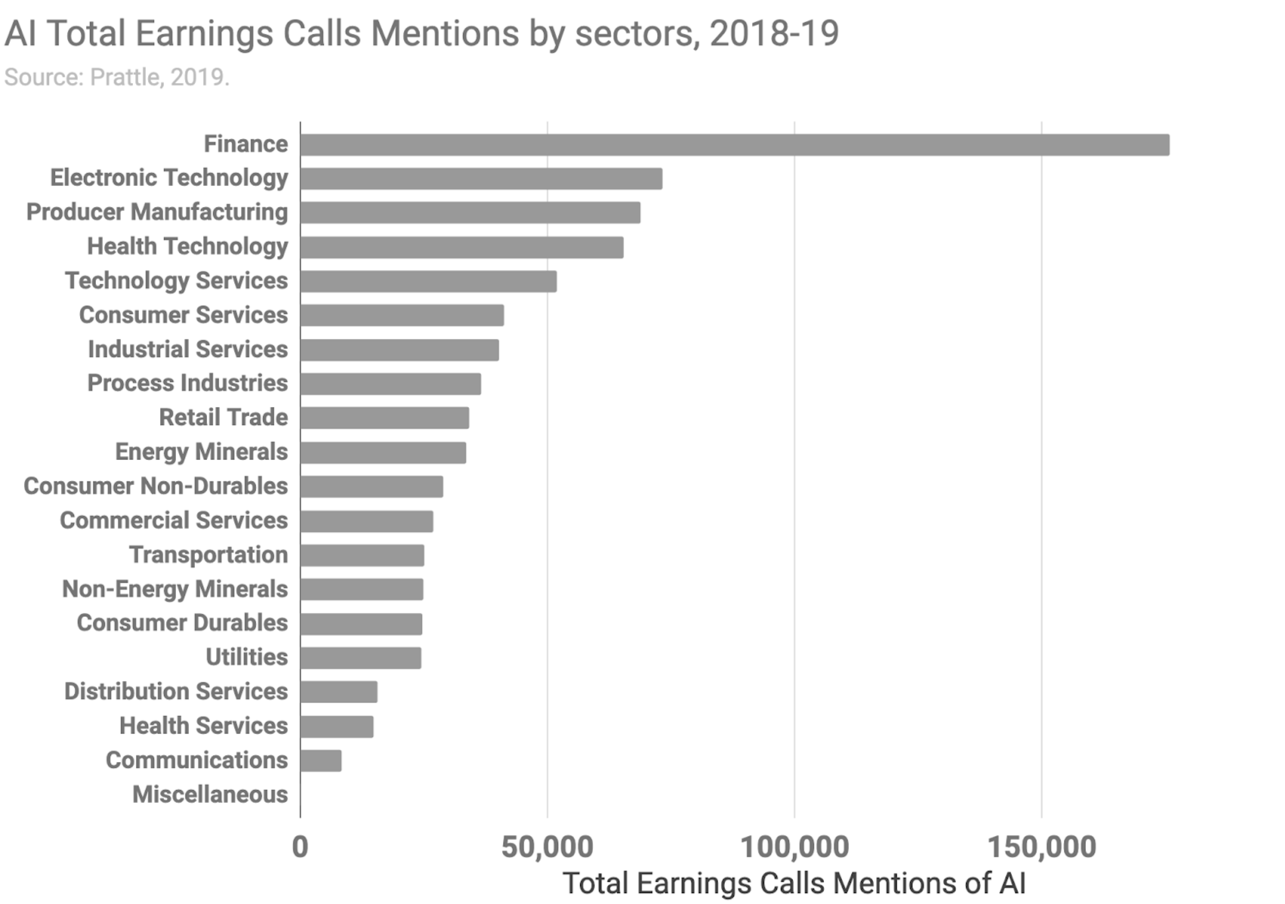


Fig. 7.4b.

## Web Search and World News

The timeline below shows the relative search interest by month of web searchers in the United States from January 2004 to August 2019 for the phrases "data science," "big data," "cloud computing," and "machine learning" using Google Trends (Figure 7.5a). Google's methodology calculates the time period with the highest amount of searching, then treats that as 100 and scales the rest accordingly.

In this analysis there is an emergence of cloud computing in 2008, which is replaced as the term of art by "big data" which starts taking off in 2011. Machine learning and data science both take off together in 2013, following technical advances in deep learning like the results on the 2012 ImageNet competition.

US search interest for “data science,” “big data,” “cloud computing” and “machine learning” via Google Trends
Source: Google Trends, GDELT, 2019.

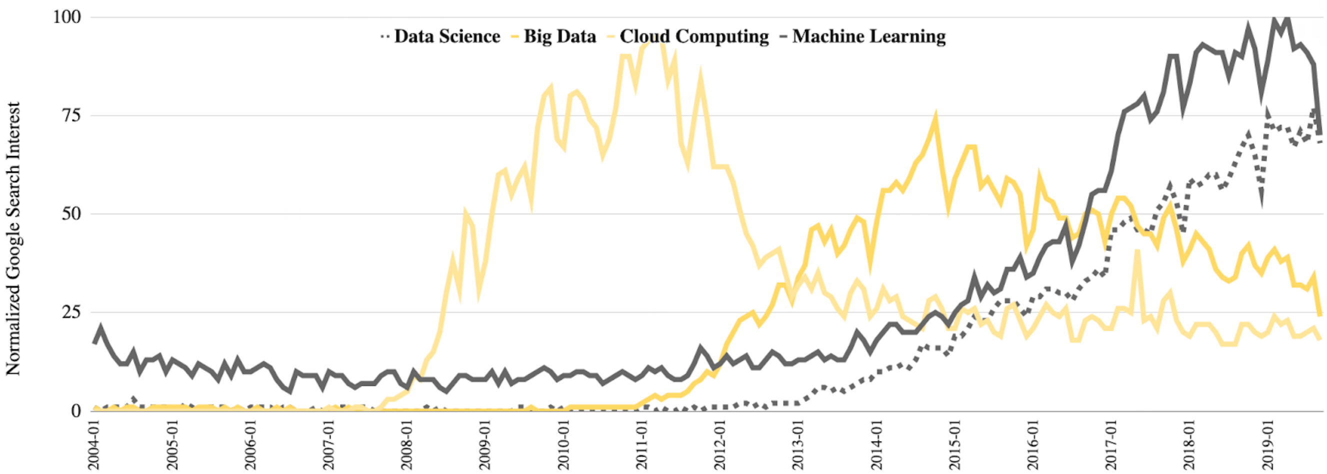


Fig. 7.5a.

## Web Search and World News

The timeline below compares some of the terminology used to refer to AI today: "machine learning," "deep learning," "artificial intelligence", as well as the term for the most popular deep learning software, "TensorFlow" (Figure 7.5b). Google's TensorFlow package is now searched just as often as AI and both have been slowly decreasing in search interest since early 2018. After taking off in 2013, deep learning plateaued in late 2017, around the time that searches for machine learning began to slowly level off.

Using data from the GDELT Project, the timeline below shows the percentage of worldwide news coverage in 65 languages monitored by GDELT by day that contain those same four terms since January 1, 2017, using a 7-day rolling average to smooth the data. This graph shows that online news coverage of cloud computing and big data has steadily declined and data science and machine learning have increased. This frequency of queries suggests that "big data" retains its allure as a media term for journalists covering the latest data-driven news, but that in both searches and news coverage, Machine Learning is the term *du jour*.

US search interest for “machine learning,” “deep learning,” “TensorFlow” and “artificial intelligence” via Google Trends
Source: Google Trends, 2019.

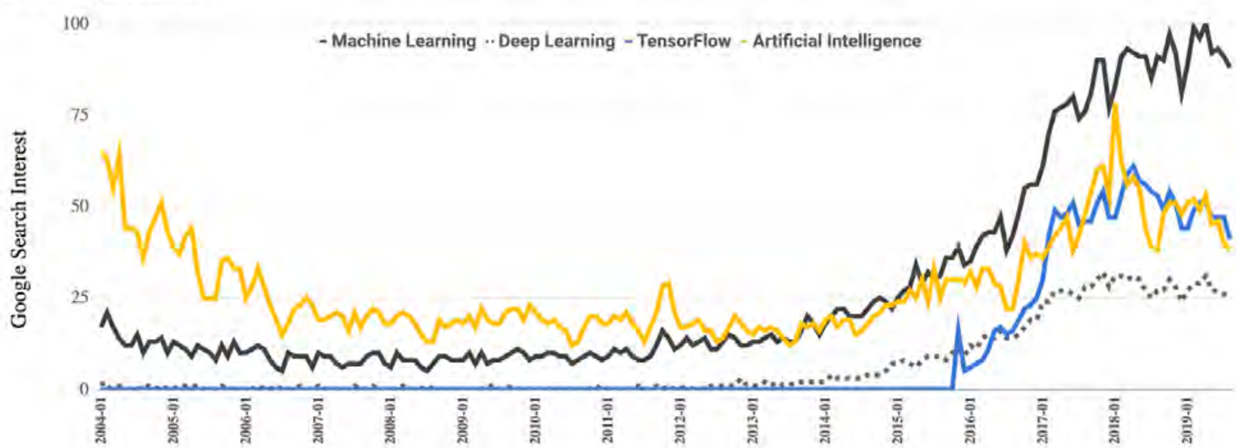


Fig. 7.5b.

Percent of worldwide news coverage monitored by GDELT that mentioned “data science,” “big data,” “cloud computing” and “machine learning”
Source: GDELT, 2019.

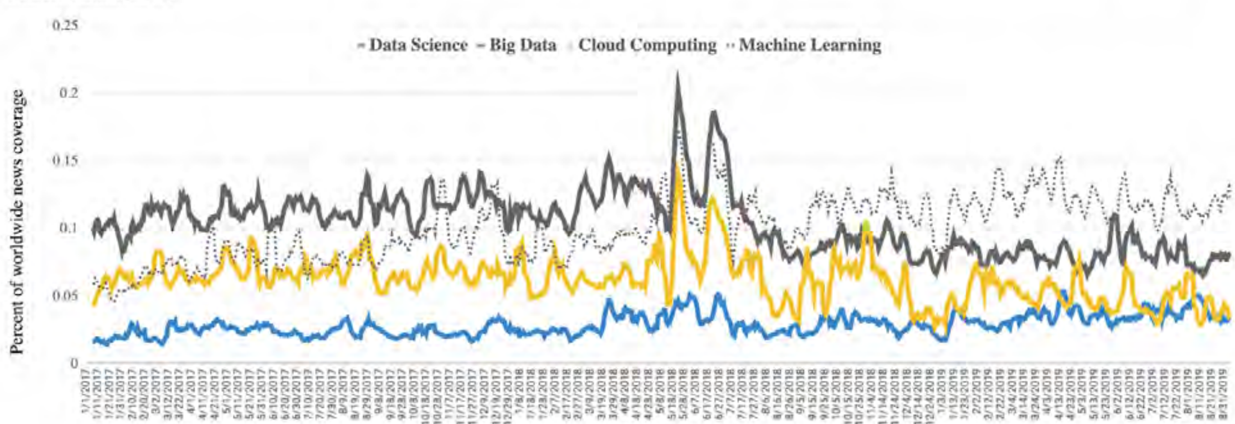


Fig. 7.5c.

## Web Search and World News

Looking at online news coverage, the timeline below shows that "Artificial Intelligence" is the clear winner, followed by Machine Learning and deep learning (Figure 7.5d).

When the media covers AI, what does media think AI is influencing? The bar chart below shows the percentage of articles monitored by GDELT containing either "artificial intelligence" or "machine learning" or "deep learning" that also contained either "job" or "jobs" or "employment" or "unemployment," the percentage that contained either "killer robot" or "killer robots" or "autonomous weapon" or "autonomous weapons," and the percentage that contained either "bias" or "biases" or "biased" (Figure 7.5e).

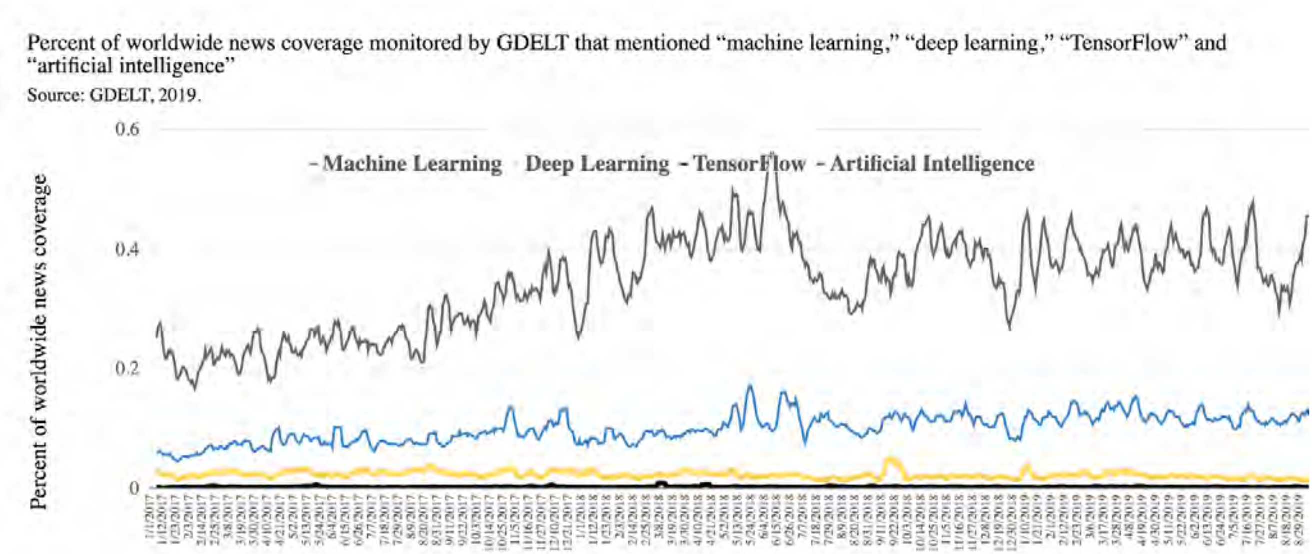


Fig. 7.5d.

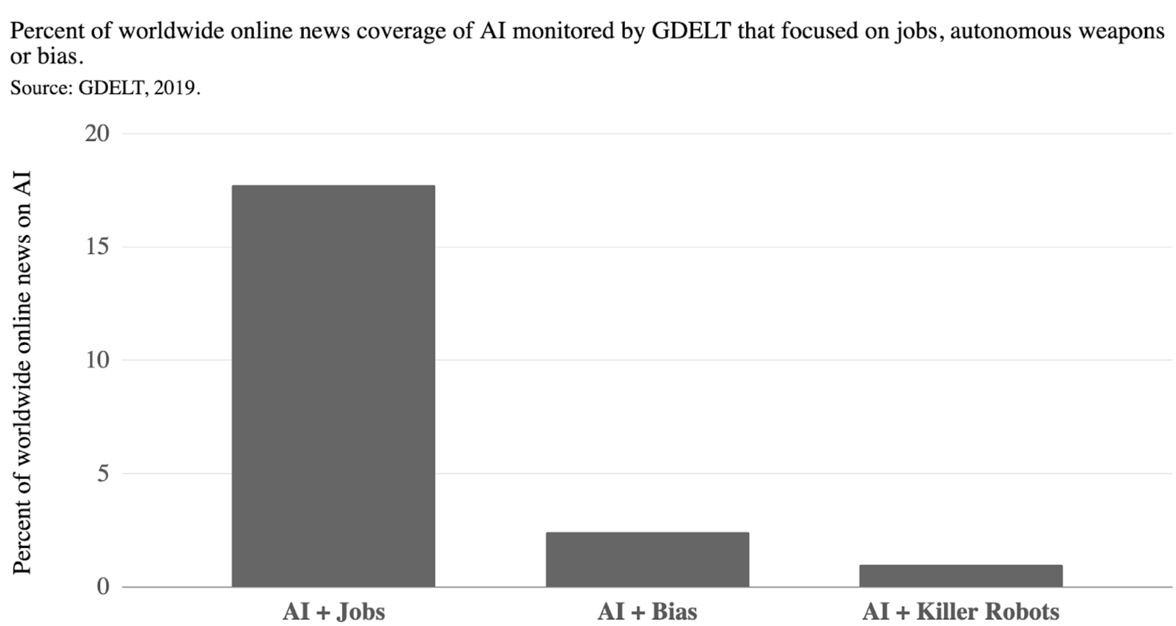


Fig. 7.5e.

## Web Search and World News

Articles addressing AI's potential impact on jobs, including concern over the potential for AI to displace human jobs, accounted for 17.7% of all AI-related coverage GDELT monitored over the past two and a half years. Killer robots accounted for just 0.99% and bias issues accounted for just 2.4% of AI discussions (Figure 7.5f).

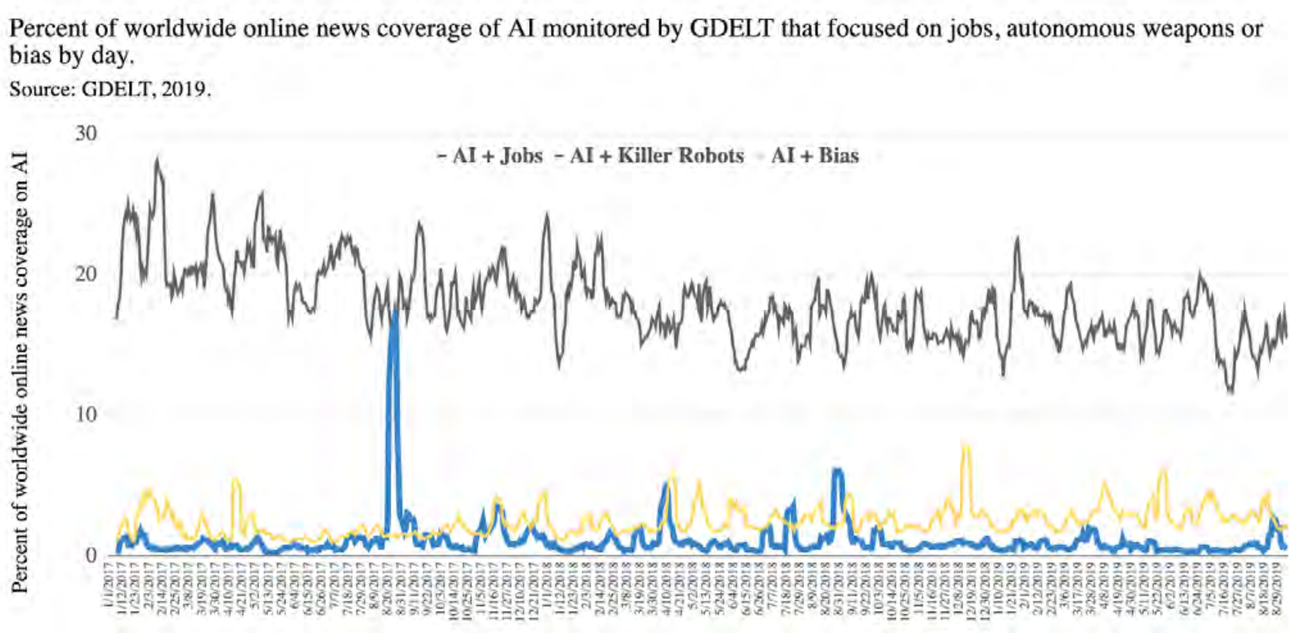


Fig. 7.5f.

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# Chapter 8: Societal Considerations

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# Introduction

This chapter begins by identifying the topics in ethical challenges mentioned in 59 Ethical AI Principle documents based on a dataset compiled by PricewaterhouseCoopers (PwC). The chapter also documents the key topics discussed in global news media on AI and Ethics based on LexisNexis data and Quid. AI use cases supporting each of the 17 United Nations (UN) Sustainable Development Goals (SDGs) are identified based on curated data from the McKinsey Global Institute (MGI).

## Ethical Challenges

AI systems raise a broad variety of ethical challenges that are now the concern of government, public interest organizations, NGO's, academia, and industry. Efforts to identify these challenges and to develop guiding principles for ethically and socially responsible AI systems are emerging from each of these sectors,. This snapshot of some such t efforts was derived from an analysis of more than 100 documents.

PricewaterhouseCoopers (PwC) compiled a dataset of ethical challenges (based on topic modeling) by looking at ethical AI guidelines across for 110 documents, of which only 59 were deemed to discuss a set of AI principles. Many were simply reviews or recommendations, and were not included in the analysis. The list of organizational documents and the list of principles is available in the Appendix.

A view of ethical AI frameworks over time is plotted identifying Associations and Consortiums, Industry and Consultancy groups, Governments, Tech Companies, and Think Tanks/Policy Institutes and Academia (Figure 8.1a). It is interesting to note that initial impetus for Ethical Principles sprang from Associations and Consortiums, with other organizations subsequently releasing their respective AI Principles in 2018 and 2019.

**Top 3 Ethical Challenges, Associations and Consortiums, Governments, and Tech Companies**

**Associations and Consortiums (19 documents)**
1.) Interpretability & Explainability is cited in 95% of frameworks.
2.) Fairness is cited in 89% of frameworks.
3.) Transparency is cited in 84% of frameworks.
**Governments (13 documents)**
1.) Interpretability & Explainability, Fairness, and Transparency are each cited in 92% of frameworks..
**Tech Companies (11 documents)**
1.) Fairness is cited in 100% of frameworks.
2.) Transparency is cited in 81% of frameworks.
3.) Accountability is cited in 72% of frameworks.
**Think Tanks/Policy Institutes and Academia (8 documents)**
1.) Fairness is cited in 100% of frameworks.
2.) Human Control is cited in 88% of frameworks.
3.) Interpretable & Explainable Model is cited in 88% of frameworks.
**Industry and Consultancy (8 documents)**
1.) Transparency is cited in 88% of frameworks.
2.) Fairness, Data Privacy, and Reliability, Robustness, and Security are each cited in 75% of frameworks.

**Number of Ethical AI Frameworks Produced 2016-2019, by Type of Organization**

Source: PwC based on 59 Ethical AI Principle documents.

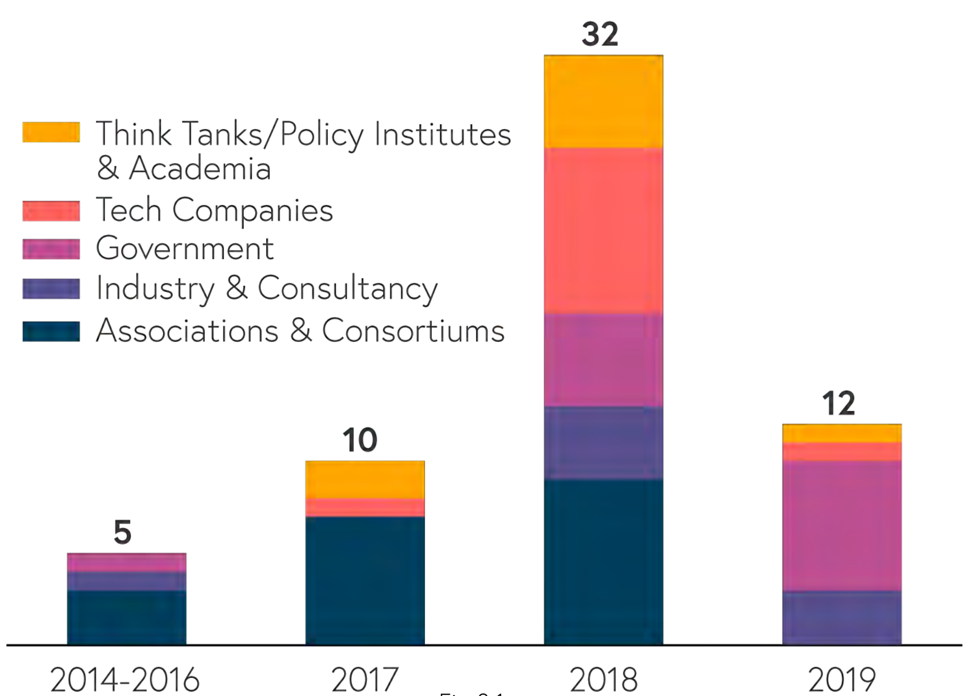


Fig 8.1a.

[Societal_Considerations_Technical_Appendix]
[Access_Data]

## Ethical Challenges

Twelve ethical challenges were mentioned across many ethical AI framework documents. This list is non-exhaustive, and many important ethical issues -- including justice, economic development, poverty reduction, and inequality, are missing. Even so, these 12 ethical challenges indicate where attention has been focused:

- Accountability
- Safety
- Human Control
- Reliability, Robustness, and Security
- Fairness
- Diversity and Inclusion
- Sustainability
- Transparency
- Interpretability and Explainability
- Multi Stakeholder engagement
- Lawfulness and Compliance
- Data Privacy

To communicate the thrust of the ethical AI issues to the general public, the bar graph shows the incidence of identified ethical challenges across 59 AI Principles documents (Figure 8.1b). It shows that Fairness, Interpretability and Explainability, Transparency are most mentioned across all documents studied.

**Ethical Challenges covered across AI Principle Documents**

Source: PwC based on 59 Ethical AI Principle documents.

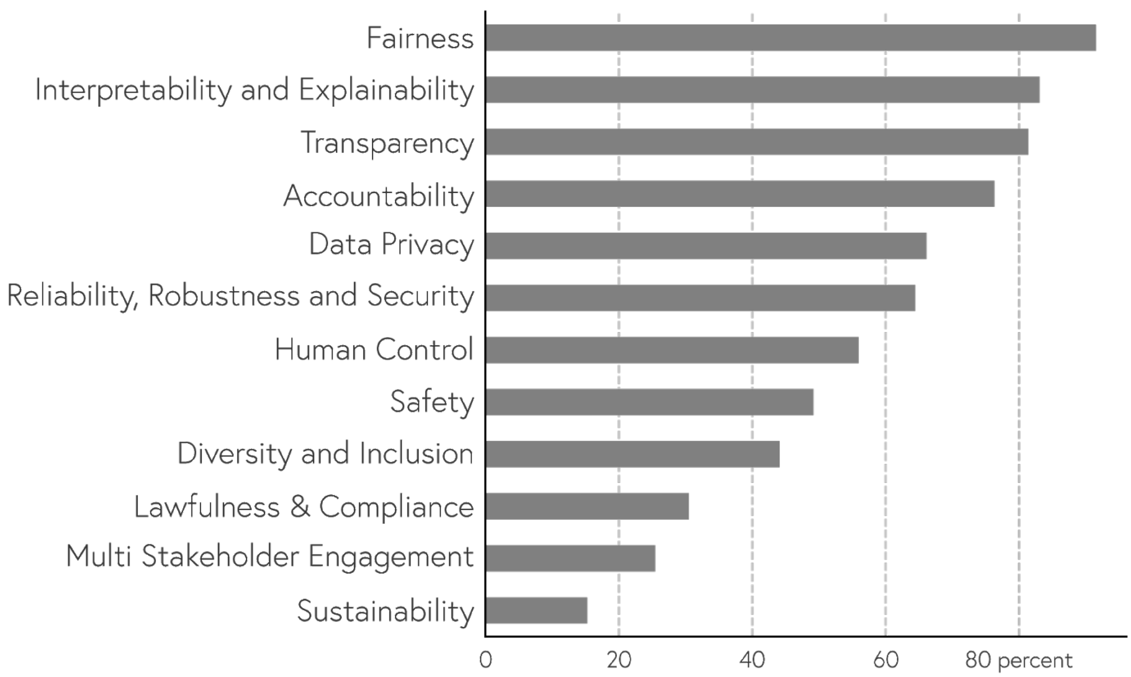


Fig 8.1b.

*"Research around Ethical AI, especially on fairness, accountability, and transparency (FAT) of machine learning models has grown significantly in the past couple of years. While there is a broad consensus emerging on the core set of principles associated with ethics and AI, the contextualization of these principles for specific industry sectors and functional areas is still in its infancy. We need to translate these principles into specific policies, procedures, and checklists to make it really useful and actionable for enterprise adoption."*

Anand Rao, Global AI Lead, PwC

## Ethics and AI: Global News Media

Global news coverage of Artificial Intelligence has increasingly shifted toward discussions about its ethical use. To better understand how these narratives are taking shape, we leveraged Quid to search the archived news database of LexisNexis for news articles from 60,000 global English news sources and over 500,000 blogs on AI ethics from August 12, 2018 to August 12, 2019 (see Appendix for more detail on search terms).

Based on keywords defined by Harvard (seen here), Quid included search terms such as human rights, human values, responsibility, human control, fairness, discrimination or non-discrimination, transparency, explainability, safety and security, accountability, and privacy related to AI technology. Then, we selected the 10,000 most relevant articles using the platform's NLP algorithm and visualized unique articles.

Each node (or dot) on a Quid network map represents a single news article. Links connecting these articles denote articles that share similar language. When a large number of similar articles are identified and linked, clusters form to reveal unique topics. The Quid algorithm classified the resulting media narratives into seven large themes based on language similarity: **Framework and Guidelines** (32%), **Data Privacy Issues** (14%), **Facial Recognition** (13%), **Algorithm Bias** (11%), **Big Tech Advisory on Tech Ethics** (11%), **Ethics in Robotics and Driverless Cars** (9%), and **AI Transparency** (6.7%).

**Quid network with 3,661 news articles on AI Ethics from August 12, 2018 to August 12, 2019. Colored by theme. Labeled by theme.**

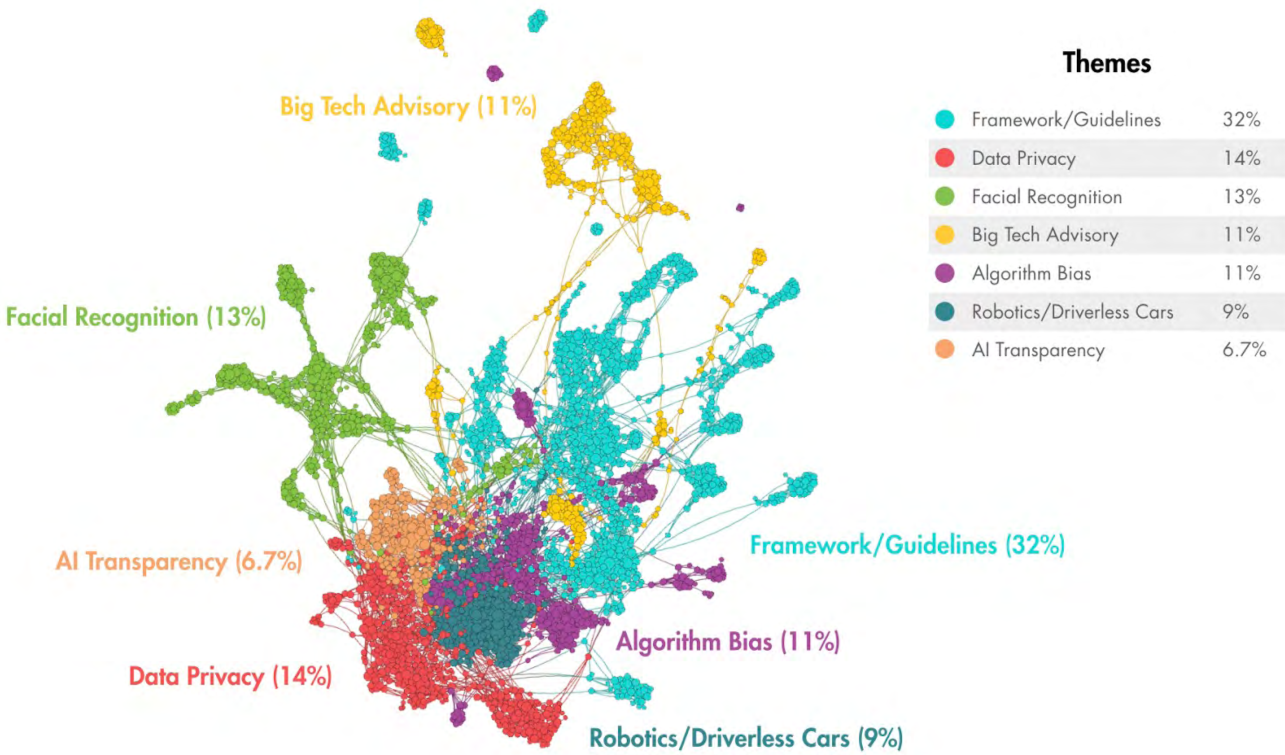


Fig. 8.2a.
Appendix: How to Red a Quid Network

## Ethics and AI: Global News Media

These results indicate that the global media conversation on AI Ethics in 2019 is largely about AI ethics frameworks or guidelines led by governments, intergovernmental organizations, and research institutes (Figure 8.2a). Within the last year, nearly a third (32%) of all news articles covered AI guidelines proposed by governments or other large policy institutes, including those by the European Union and the Organisation for Economic Co-operation and Development (OECD). A smaller, but not an insignificant chunk of the conversation (11%) also included commentary from advisory groups attached to tech giants such as Google, Facebook, and Microsoft.

When filtering for ethics discussions around specific AI technologies, facial recognition dominated the attention of the news media, with 13% of all articles (Figure 8.2a). his cluster's position on the periphery of the larger AI ethics narrative indicates a high degree of uniqueness from the rest of the conversation. Public concerns over the technology's threat to data privacy have grown over time, driven by news of mistaken identities during crime surveillance, biometric scans that can be applied to videos or photos without consent, and the idea of data ownership as it relates to social media platforms that utilize the technology.

Countries differ significantly with respect to which AI ethical issues (as defined by Harvard here) they give most news coverage. While media sources based in the US or UK had more balanced coverage between categories, others reflected specific focus areas (Figure 8.2b). In Switzerland, for example, 45% of all articles covered guidelines and frameworks on AI development, while 44% of Chinese news focused on safety and security, and 48% of articles in Singaporean sources explored transparency and explainability.

### Most mentioned ethics categories by Source Country

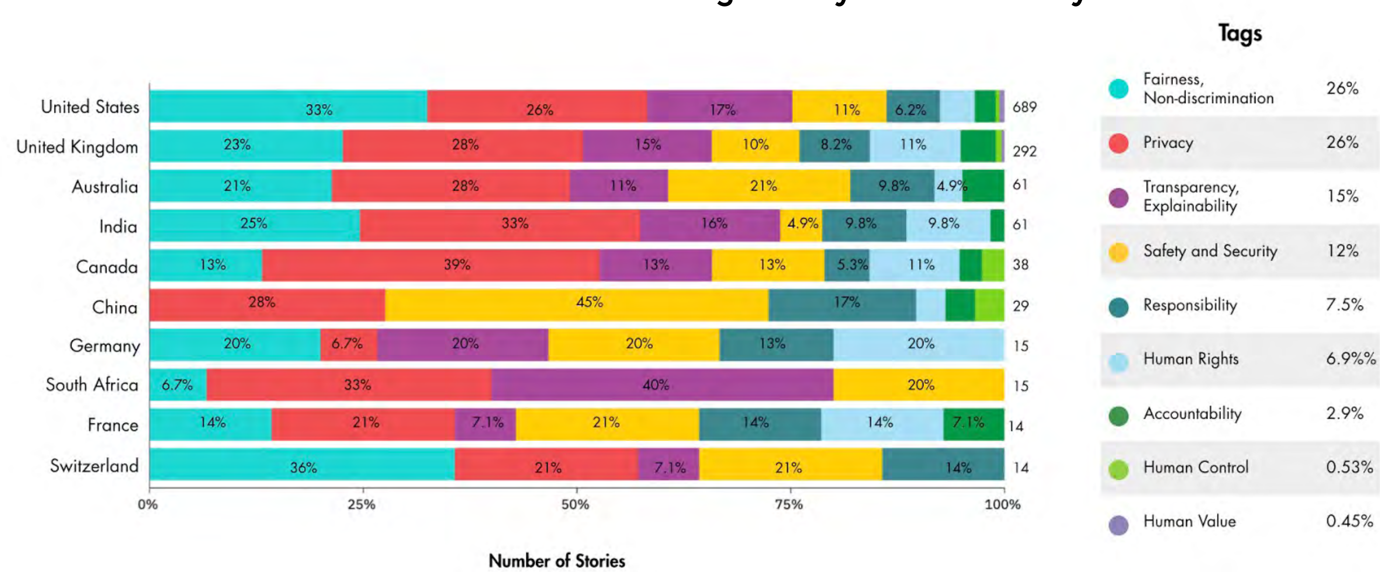


Fig. 8.3b.

## Applications of AI for Sustainable Development

Artificial intelligence, while not a silver bullet, has the potential to help contribute to multi-pronged efforts to address some of society's most pressing challenges.

The mapping of AI use cases to the UN Sustainable Development Goals (SDGs) that follows are derived from a library of approximately 160 AI for social good use cases collected by the McKinsey Global Institute and Noble Intelligence, McKinsey's initiative to use AI for humanitarian purposes. The library of use cases is not comprehensive, but reflects a selection of use cases, typically in domains with initial evidence of possible applications. AI deployments in some form were identified for about one-third of use cases in the library; in about three-quarters of use cases, deployments of solutions employing some level of advanced analytics were observed, most (if not all) of which could further benefit from using AI.

To build the use case library, MGI took a two-pronged approach: from a societal point of view, MGI sought to identify key problems known to the social sector community and determine where AI could aid efforts to resolve them; from a technological point of view, MGI took a curated list of 18 AI capabilities and sought to identify which types of social problems they could best contribute to solving. Each use case highlights a meaningful problem that can be solved by an AI capability or some combination of AI capabilities. The library is not comprehensive, but it nonetheless showcases a wide range of problems where AI can be applied for social good. MGI's full discussion paper can be found at Notes from the AI frontier: Applying AI for social good.

## Applications of AI for Sustainable Development

**Artificial intelligence has applicability across all 17 of the United Nations Sustainable Development Goals**

The UN SDGs are a collection of 17 global goals set by the United Nations for the year 2030, for poverty alleviation, improving health and education, reducing inequality, preserving the environment, and boosting economic growth, amongst other priorities. AI use cases have the potential to support some aspect of each of the UN SDGs. The chart below indicates the number of AI use cases in MGI's library that could support each of the UN SDGs (Figure 8.3a).

SDG 3, "Ensure healthy lives and promote well-being for all at all ages", could be supported by the highest number of use cases in MGI's current library. A number of use cases that leverage AI support medical diagnoses: for example, researchers at the University of Heidelberg and Stanford University have created an AI system to visually diagnose skin cancer that outperformed professional dermatologists. There are also potential cases where AI can be used to monitor, track and predict outbreaks of communicable diseases. For instance, Data Science for Social Good and McKinsey's Noble Intelligence initiative developed an algorithm to identify children most at risk of not receiving the measles vaccination, allowing physicians to spend more time educating and following up with these families.

There are also a number of AI use cases that could support SDG 16, "Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels." The use cases cover domains ranging from helping individuals verify and validate information, providing improved security through detection and prediction of violence, addressing bias to ensure fair and equal access to justice, to optimizing the management of public and social sector institutions. For example, AI could be used to automate question response or provision of services through digital channels, helping to improve government interactions with citizens.

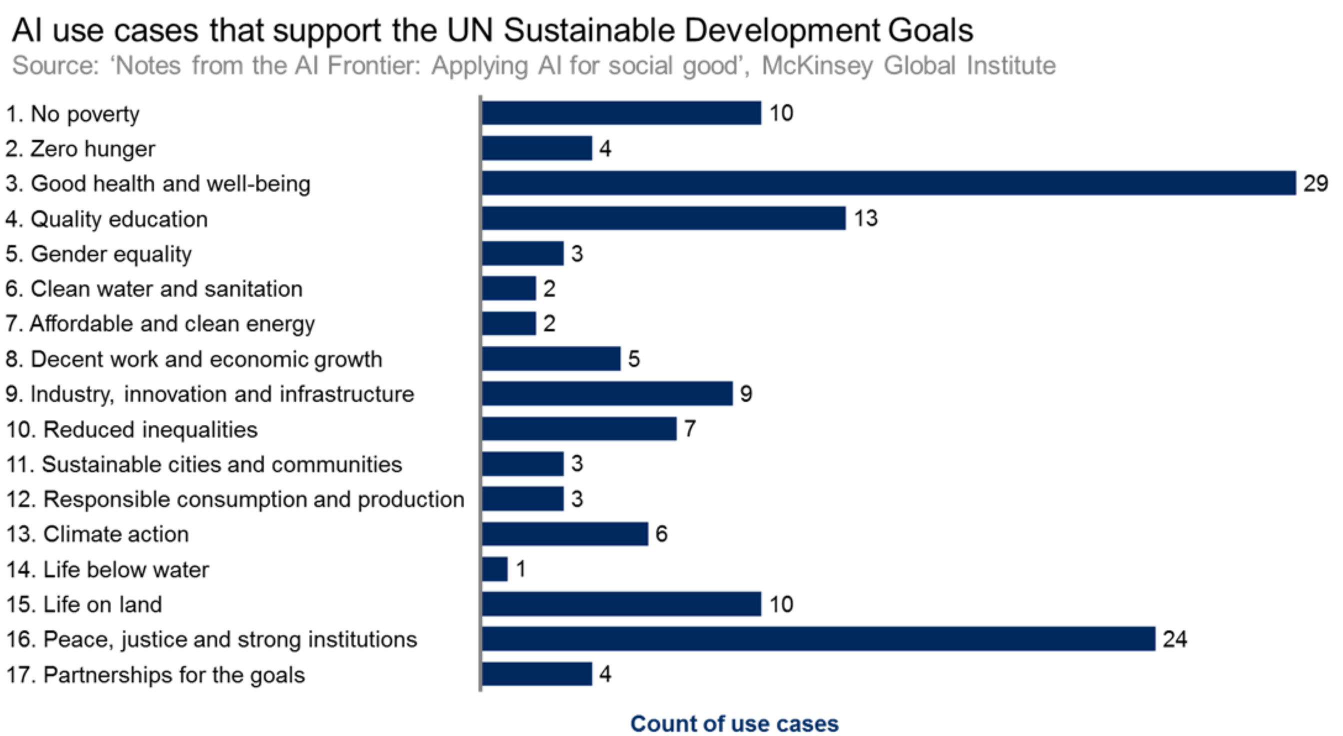


Fig. 8.3a.
NOTE: This chart reflects the number and distribution of use cases and should not be read as a comprehensive evaluation of AI potential for each SDG; if an SDG has a low number of cases, that is a reflection of our library rather than of AI applicability to that SDG.

## Applications of AI for Sustainable Development

### AI is applicable to driving a subset of targets across the UN SDGs

Each UN SDG is broken down into a list of targets, which are measured with indicators. There are 169 targets across the 17 UN SDGs. While AI use cases can be topically aligned to the SDGs, as displayed in the previous chart, further focus should be directed to the use cases that can directly drive impact towards achieving specific UN SDG targets and indicators.

By mapping AI use cases to the specific target(s) that they could contribute to achieving, MGI identified the subset of targets for which AI has some applicability to address. This analysis builds upon the ~160 use cases in MGI's library and others to identify which targets could be addressed by a solution in which AI is applied, recognizing that AI alone cannot solve any of the targets. The following chart displays the number of targets which AI could contribute to addressing, out of the total number of targets within each SDG (Figure 8.3b).

### Some AI for sustainable development use cases are being piloted, although bottlenecks exist

A number of organizations globally are piloting applications of AI for sustainable development, although there are currently few examples of deployments of AI for sustainable development at scale. For example, AI has been piloted for several applications in disaster relief by a number of organizations, including Google, Facebook, Microsoft, Planet Labs, Airbus, SAP, and others. Still, there is more to be done to sustainably adopt these AI applications for widespread use in disaster relief across multiple partners and regions.

Some AI-specific bottlenecks will need to be overcome for AI to reach its potential for social impact. These range from challenges with data (including availability, accessibility, quality, volume, labelling, and integration), accessing to computing capacity, availability and accessibility of AI talent, and the receptiveness and capabilities of organizations deploying solutions. Some efforts are underway to address this, especially to address accessibility of data for social good, including the Global Data Commons and UN Global Pulse.

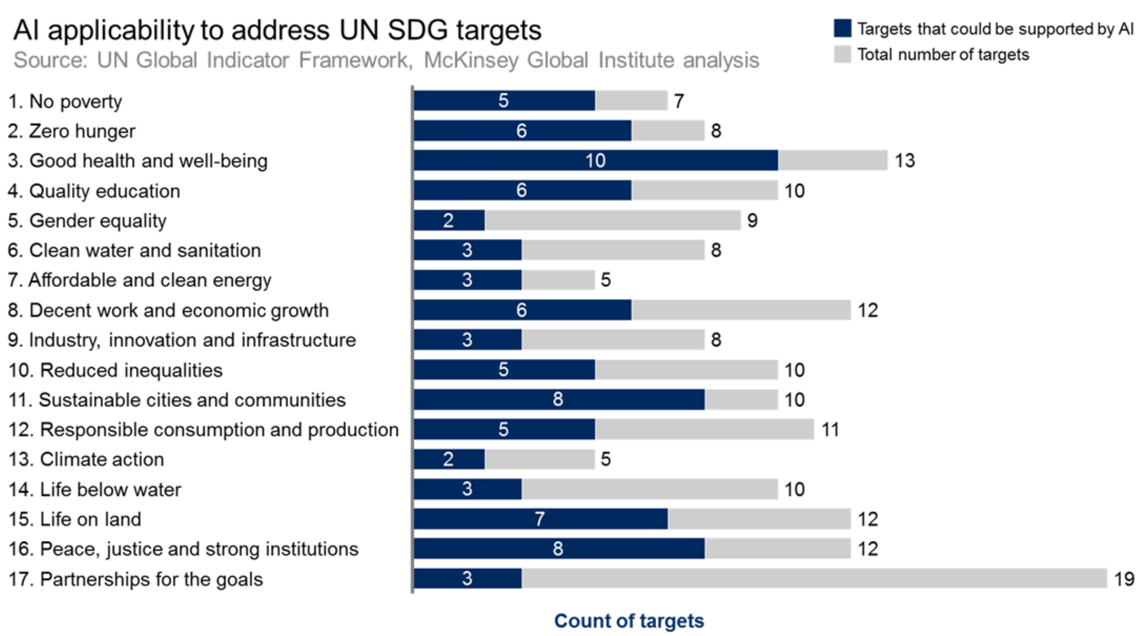


Fig. 8.3b.

## Measurement Questions

- How can standardized granular data on AI use cases that impact fairness, human rights, and human dignity be generated?
- How can AI development be integrated into frameworks with social goals, to better plan AI technical development alongside social impacts?
- What measurements can be developed to assess how AI might generate societal threats as well as opportunities?

## Chapter Preview

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# Chapter 9: National Strategies and Global AI Vibrancy

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# Introduction

This chapter begins by identifying the topics mentioned in official National AI Strategy Radar (NAISR) documents from PricewaterhouseCoopers (PwC). The Appendix documents detailed policy milestones and links to country specific policy documents. The Global AI Vibrancy Tool - a country weighting tool is introduced to aid comparison of countries' global activities, including both a cross-country perspective as well as an intra-country drill down. The tool allows the reader to set the parameters and obtain the perspective they find most relevant. Country pages document key policy milestones accompanied by a country data page for select nations.

There are limitations to overcome in future years' reports. For example, it would be important to know how many official government documents on AI have been published by governments that haven't been translated into English, to help understand what is missing. Similarly, the Global AI Vibrancy will improve with feedback from the community, but also (a) diverse new metrics, (b) more coverage for more developing countries, (c) deeper understanding of causal relationship to inform data-driven decision-making on AI at the national or sub-national level.

## National Strategies

The number of official AI strategy documents (both global and national reports) has been increasing over the last few years (Figure. 9.1a). There are several efforts to track and collate national AI strategy documents, including those from UNICRI-FutureGrasp and Future of Life Institute. Other publications have been released by global think tank and thought leadership institutions mentioning the priorities of various nations. These documents can be long and difficult to distill. To support this effort, understand the commonalities and differences of these strategy and overview documents, and observe changes over time, PricewaterhouseCoopers (PwC) has created the National AI Strategy Radar (NAISR) that utilizes natural language processing (NLP) rather than relying on humans to read through the documents. Topic modelling on the documents is conducted to understand the major themes and topics in these documents. Details on country AI policy milestones and methodology can be found in the NAISR Appendix. The non-exhaustive list of global AI reports, strategies and country strategies documents used in the analysis is available here.

Based on 37 analyzed documents, the bar chart shows the percentage of documents mention the topic clusters identified by the topic model. Academic Partnership is present in 94% of the documents, AI R&D in 48% and AI Governance mentioned in over 42% of the documents. Consumer Protection and Fairness is mentioned the fewest times, appearing in 2% of the documents (Figure 9.1b).

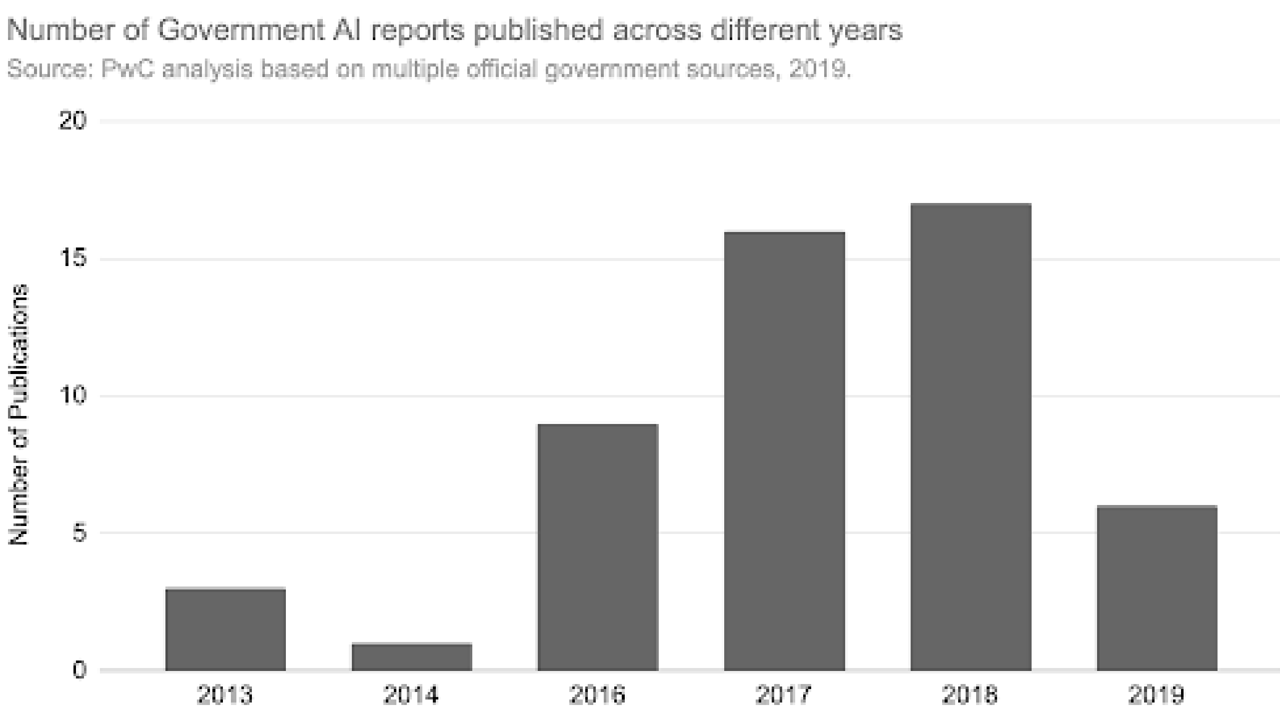



Fig. 9.1a.
Note: Data as of August 2019

## National Strategies

**Percent of Global and National AI strategy documents mentioning Topics (%)**
Source: PwC based on 48 AI Strategy documents.

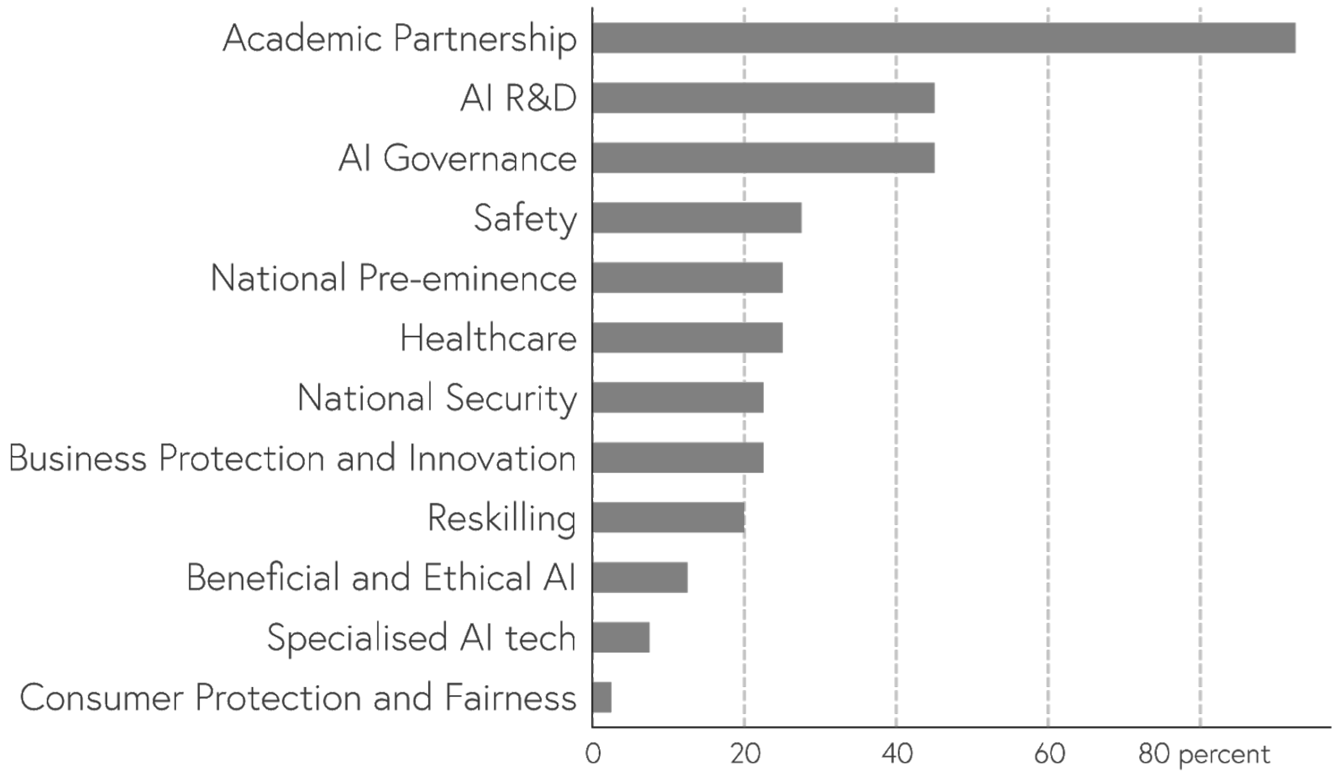



Fig. 9.1b.
Note: Data as of August 2019

[National_Strategies_AI_Vibrancy_Technical_Appendix]
[Access_Data]

## National Strategies

A world heatmap shows the number of mentions of countries across the globe in the global sample of AI strategy documents (Figure. 9.2). Countries are developing new strategies constantly. Limitations will exist in sampling official documents until the Index builds an automated crawler for official government AI agencies. Official national strategies documents mentioning Latin America, Africa, and Central Asia are still being acquired, as many countries in these areas are actively exploring AI strategies. The traceability matrix showing the coverage of topics for all documents in the sample (see Appendix Graph). Due to current language limitations, only reports in English or translated to English were considered in this analysis. The 2020 report is building greater translation capacities.

**World Map of Countries mentioned in AI documents (official and from major institutions)**

Source: PwC NAISR, data as of August 2019 refresh; multiple strategies have been released since

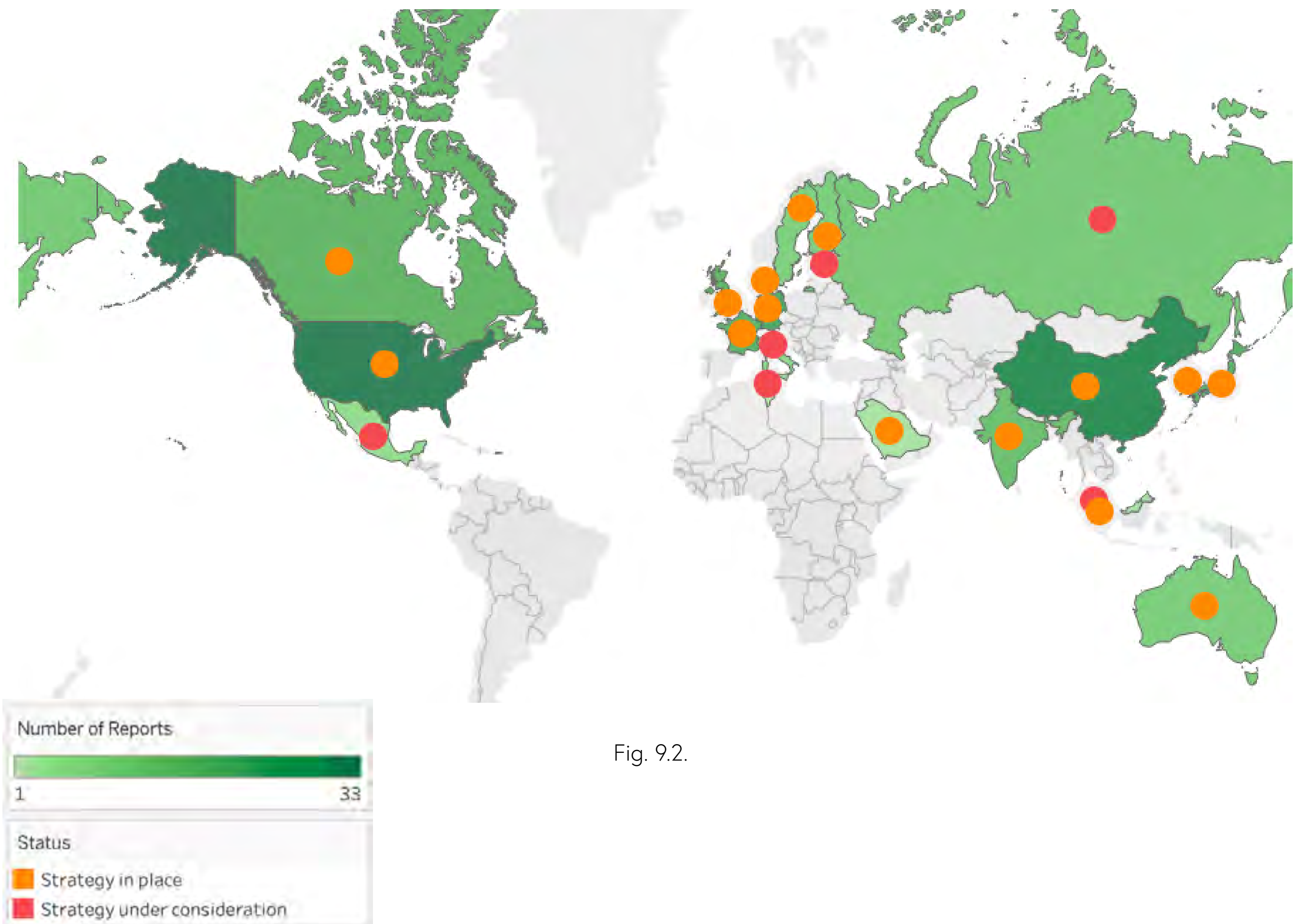



Fig. 9.2.

## Global AI Vibrancy Tool

This section summarizes the methodology of the Global AI Vibrancy Tool. The Global AI Vibrancy Tool covers over 28 countries across 34 metrics grouped into three high-level pillars of AI starting in 2015: Research and Development, Economy, and Inclusion. The aggregate indicators are based on several million individual underlying variables, taken from a wide variety of datasources. The data reflect the views on AI from primary data sources and survey from private, public, and NGO sectors worldwide. The metrics are scaled between (0-100) to indicate the relative position of a given country in the global distribution specific to each metric. The Global AI Vibrancy Tool permits meaningful cross country and over time comparisons based on the readers' weighting preference. The underlying source data with detailed description for each indicator are available at vibrancy.aiindex.org.

**Country Coverage**
The 28 countries covered in the Global AI Vibrancy Tool were selected based on an aggregate data availability threshold of at least 70% (24 out of 34 variables) at the sub-pillar level data availability. The most recent data points for each country were considered in the calculation between 2015 and 2018 as a cutoff year. Meanwhile, each variable had to pass a country-based availability threshold of 50% (28 out of 123 countries). In order to provide transparency and replicability, there was no imputation effort to fill in missing values in the data set. Missing values were noted with 'n/a' and were not considered in the calculation of sub-pillar scores.

**Data Sources and Definitions**
The abstraction below shows the high-level pillar and sub-pillars covered currently by the Global AI Vibrancy Tool. Each sub-pillar is composed of individual indicators reported in the Global AI Vibrancy codebook. The sub-pillar highlighted in a color denote that metrics about these dimensions are not available (or have not been incorporated) for this version of the Global AI Vibrancy Tool.

The details on data, sources and definition are available in the Appendix. There are 21 metrics used under Research and Development, 10 metrics under Economy, and 5 metrics available under Inclusion.

# Global AI Vibrancy

[topics_covered]

## Research and Development

- Publication
- Patent
- Conferences
- Education
- Technical Performance

## Economy

- Startup Investment
- Corporate Activity
- Public Investment
- Jobs and labor
- Robotic Sales and Trade
- Skill Penetration
- National Strategies

## Inclusion

- Gender Diversity
- Public Perception
- Threats

**Note: The sub-pillar highlighted in a color denote that metrics about these dimensions are not available (or have not been incorporated) for this version of the Global AI Vibrancy Tool.**

## Global AI Vibrancy: Country Weighting Tool

To aid data-driven decision-making and policy strategies, the Global AI Vibrancy is available as a web tool. The detailed datasets are available here and on **vibrancy.aiindex.org**.

The webtool allows users to adjust weights to each metric based on their individual preference. The **default settings** of the tool allow the user to select between three weighting options:

**All weights to midpoint**

This button assigns equal weights to all indicators.

**Only absolute metrics**

This button assigns maximum weights to absolute metrics. Per capita metrics are not considered.

**Only per capita metrics**

This button assigns maximum weights to per capita metrics. Absolute metrics are not considered.

The user can adjust the weights to each metric based on their preference.

The charts automatically update when any weight is changed.

The user can select "Global" or "National" view to visualize the results. The "Global" view offers a cross country comparative view based on the weights selected by the user. The "National" view offers country deep dive to assess which AI indicators (or attributes) a given country is relatively better at. The country-metric specific values are scaled (0-100), where 100 indicates that a given country has the highest number in the global distribution for that metric and conversely small numbers like 0 or 1 indicates relatively low values in the global distribution This can help identify areas for improvement and identify national policy strategies to support a vibrant AI ecosystem.

The heatmap below shows 28 countries against 34 metrics in 2018 (Figure 9.4). The color spectrum is between scaled values between 0-100 for each metric (light blue to dark blue spectrum). For example, 100 (blue) for Singapore in AI journal publications in per capita terms represents that Singapore has the highest number. Similarly, black indicates "NA" to denote that data is unavailable for a given country.

**AI Vibrancy: Normalized Distribution (0-100) for 28 Countries on 34 Metrics, 2018**

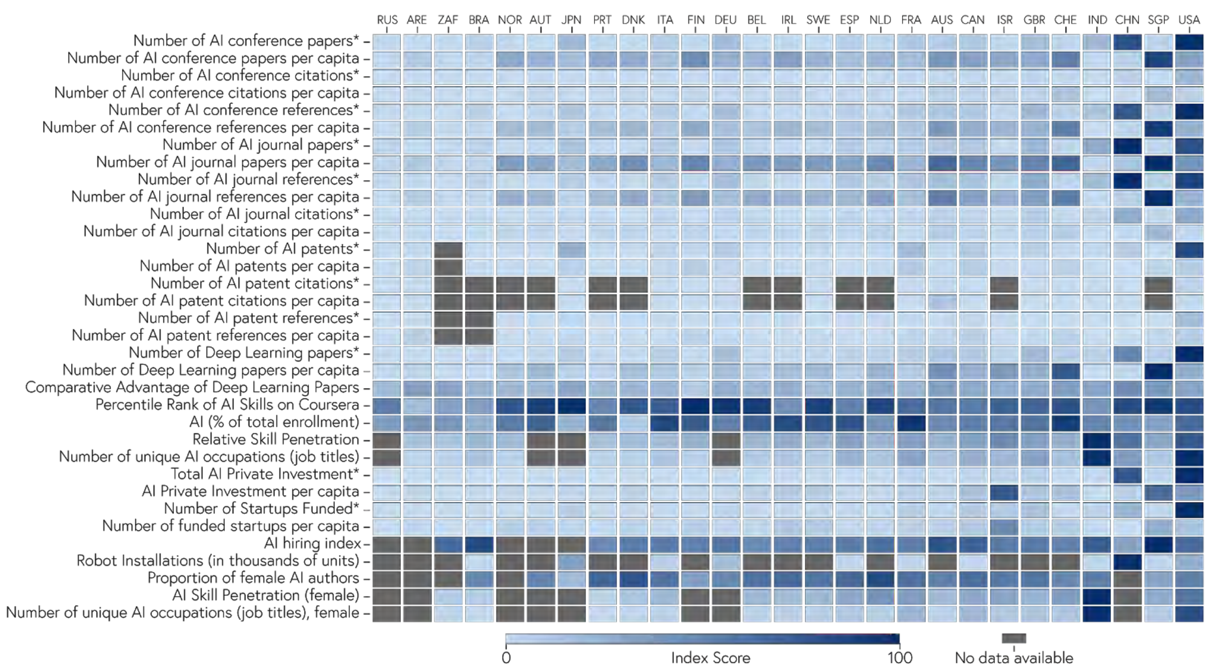



Fig. 9.4.

# Country Pages

Country pages provide succinct details on country policy milestones followed by a data page on the respective country. Here, the country policy details are limited to eight countries (key advanced economies and emerging markets) in addition to stock taking of multilateral and regional AI policy developments. Detailed policy milestones with links to official national AI documents are available for over 26 countries is available in the Appendix. The short country policy discussion is followed by country data page so readers can easily lookup available indicators for 2018 to inform country decisions grounded in data.

Brazil
China
France
Germany
India
The Netherlands
Singapore
The United States
Multilateral Regional AI Policy

## Country Page: Brazil

In Brazil, broader innovation or government transformation strategies include, but do not focus on, AI. Brazil has not yet published a dedicated artificial intelligence strategy, but the Brazlian government has addressed AI through related initiatives:

- **2017**. Brazil launched the Internet of Things (IoT) National Action Plan. The plan is aimed at positioning the country in the forefront of technology development within the next five years, largely by utilizing AI advancements. Emphasis will be made on health, smart cities, industrial, and rural areas.

- **2018**. The Brazlian government launched the E-Digital strategy. The strategy addresses digital transformation, including AI, while protecting its citizens rights and maintaining privacy, developing an action plan for new technologies, and working with other countries to develop new technologies.

To date, Brazil has most notably implemented AI in facial recognition systems (mainly in criminal establishment and airports). Courts are also being increasingly helped by artificial intelligence technologies, with a focus on automated decision-making, identifying inconsistencies in legal data, analyzing hiring processes, national trading and investments.

# Brazil

## Research and Development

| Conference Publications | Scaled (0-100) |
|---|---|
| 1. Number of AI conference papers* | 7 |
| 2. Number of AI conference papers per capita | 4 |
| 3. Number of AI conference citations* | 0 |
| 4. Number of AI conference citations per capita | 0 |
| 5. Number of AI conference references* | 6 |
| 6. Number of AI conference references per capita | 2 |
| **Journal Publications** | |
| 7. Number of AI journal papers* | 5 |
| 8. Number of AI journal papers per capita | 4 |
| 9. Number of AI journal citations* | 1 |
| 10. Number of AI journal citations per capita | 0 |
| 11. Number of AI journal references* | 5 |
| 12. Number of AI journal references per capita | 2 |
| **Innovation > Patents** | |
| 13. Number of AI patents* | 0 |
| 14. Number of AI patents per capita | 0 |
| 15. Number of AI patent citations* | NA |
| 16. Number of AI patent citations per capita | NA |
| 17. Number of AI patent references* | NA |
| 18. Number of AI patent references per capita | NA |
| **Journal Publications > Deep Learning** | |
| 19. Number of Deep Learning papers* | 2 |
| 20. Number of Deep Learning papers per capita | 1 |
| 21. Revealed Comparative Advantage (RCA) of Deep Learning Papers on arXiv | 22 |

## Economy

| Skills | Scaled (0-100) |
|---|---|
| 22. Percentile Rank of AI Skills on Coursera | 36 |
| 23. AI (% of total enrollment) | 25 |
| 24. Relative Skill Penetration | 22 |
| 25. Number of unique AI occupations (job titles) | 14 |
| **Labor** | |
| 26. AI hiring index | 84 |
| **Investment** | |
| 27. Total Amount of Funding* | 0 |
| 28. Total per capita Funding | 0 |
| 29. Number of Startups Funded* | 1 |
| 30. Number of funded startups per capita | 0 |
| **Robot Installations** | |
| 31. Robot Installations (in thousands of units) | 1 |

## Inclusion

| Gender Diversity | Scaled (0-100) |
|---|---|
| 32. Proportion of female AI authors | 50 |
| 33. AI Skill Penetration (female) | 9 |
| 34. Number of unique AI occupations | 2 |

## Country Profile: China

- Prior to the **1980s**, China's interest in AI was focusing more on the theoretical underpinnings of AI and its possible links with contemporary political ideology. AI research in China remained fairly academic until the turn of the millennium, when large Chinese technology firms like Tencent and Baidu began to emerge, offering the opportunity for the government to collaborate with corporations on AI solutions. Since then, this link has grown, as the Chinese government works ever closer with local corporations in the collection and analysis of data for further AI development.

- **June 2017. Launch of the Next Generation AI Development Plan**
China makes one of the biggest pushes towards AI world dominance after announcing "A Next Generation AI Development Plan." For the first time, China announced its plan to become the global leader in AI by 2030.

# China

## Research and Development

| Conference Publications | Scaled (0-100) |
|---|---|
| 1. Number of AI conference papers* | 80 |
| 2. Number of AI conference papers per capita | 6 |
| 3. Number of AI conference citations* | 7 |
| 4. Number of AI conference citations per capita | 0 |
| 5. Number of AI conference references* | 76 |
| 6. Number of AI conference references per capita | 4 |
| **Journal Publications** | |
| 7. Number of AI journal papers* | 100 |
| 8. Number of AI journal papers per capita | 12 |
| 9. Number of AI journal citations* | 28 |
| 10. Number of AI journal citations per capita | 1 |
| 11. Number of AI journal references* | 100 |
| 12. Number of AI journal references per capita | 6 |
| **Innovation > Patents** | |
| 13. Number of AI patents* | 8 |
| 14. Number of AI patents per capita | 0 |
| 15. Number of AI patent citations* | 0 |
| 16. Number of AI patent citations per capita | 0 |
| 17. Number of AI patent references* | 1 |
| 18. Number of AI patent references per capita | 0 |
| **Journal Publications > Deep Learning** | |
| 19. Number of Deep Learning papers* | 49 |
| 20. Number of Deep Learning papers per capita | 3 |
| 21. Revealed Comparative Advantage (RCA) of Deep Learning Papers on arXiv | 46 |

## Economy

| Skills | Scaled (0-100) |
|---|---|
| 22. Percentile Rank of AI Skills on Coursera | 83 |
| 23. AI (% of total enrollment) | 43 |
| 24. Relative Skill Penetration | 60 |
| 25. Number of unique AI occupations (job titles) | 36 |
| **Labor** | |
| 26. AI hiring index | 33 |
| **Investment** | |
| 27. Total Amount of Funding* | 77 |
| 28. Total per capita Funding | 7 |
| 29. Number of Startups Funded* | 21 |
| 30. Number of funded startups per capita | 1 |
| **Robot Installations** | |
| 31. Robot Installations (in thousands of units) | 99 |

## Inclusion

| Gender Diversity | Scaled (0-100) |
|---|---|
| 32. Proportion of female AI authors | NA |
| 33. AI Skill Penetration (female) | NA |
| 34. Number of unique AI occupations | NA |

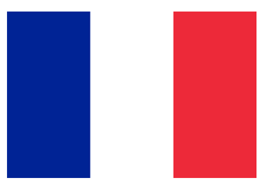
[National_Strategies_AI_Vibrancy_Technical_Appendix]
[Access_Data]

## Country Profile: France

**March 2018.** President Emmanuel Macron unveiled France's €1.5B plan to transform France into a global leader in AI. The plan draws heavily from the report, "For a Meaningful Artificial Intelligence: Towards a French and European Strategy," in which Cédric Villani, France's famed mathematician and Deputy for the Essonne, outlined a number of policies and initiatives for the government to consider.

The plan consists of four components: (1) the launch of the National Artificial Intelligence Programme, which will create a network of four or five research institutes across France; (2) an open data policy to drive the adoption and application of AI in sectors where France already has the potential for AI excellence, such as healthcare; (3) a regulatory and financial framework to support the development of domestic "AI champions;" (4) regulations for ethics.

In total, the government will invest €1.5 billion in AI by the end of the current five-year term. Details for the following have not been released, but €700 million will go towards research, €100 million this year to AI startups and companies, €70 million annually through France's Public Investment Bank, and $400 million to industrial projects in AI.The Villani report recommended focusing on four sectors (healthcare, transportation, environment, and defence).



# France

## Research and Development

| Conference Publications | Scaled (0-100) |
|---|---|
| 1. Number of AI conference papers* | 11 |
| 2. Number of AI conference papers per capita | 17 |
| 3. Number of AI conference citations* | 1 |
| 4. Number of AI conference citations per capita | 1 |
| 5. Number of AI conference references* | 11 |
| 6. Number of AI conference references per capita | 13 |
| **Journal Publications** | |
| 7. Number of AI journal papers* | 9 |
| 8. Number of AI journal papers per capita | 21 |
| 9. Number of AI journal citations* | 3 |
| 10. Number of AI journal citations per capita | 2 |
| 11. Number of AI journal references* | 12 |
| 12. Number of AI journal references per capita | 16 |
| **Innovation > Patents** | |
| 13. Number of AI patents* | 19 |
| 14. Number of AI patents per capita | 9 |
| 15. Number of AI patent citations* | 0 |
| 16. Number of AI patent citations per capita | 1 |
| 17. Number of AI patent references* | 2 |
| 18. Number of AI patent references per capita | 4 |
| **Journal Publications > Deep Learning** | |
| 19. Number of Deep Learning papers* | 7 |
| 20. Number of Deep Learning papers per capita | 10 |
| 21. Revealed Comparative Advantage (RCA) of Deep Learning Papers on arXiv | 22 |

## Economy

| Skills | Scaled (0-100) |
|---|---|
| 22. Percentile Rank of AI Skills on Coursera | 64 |
| 23. AI (% of total enrollment) | 95 |
| 24. Relative Skill Penetration | 34 |
| 25. Number of unique AI occupations (job titles) | 31 |
| **Labor** | |
| 26. AI hiring index | 55 |
| **Investment** | |
| 27. Total Amount of Funding* | 4 |
| 28. Total per capita Funding | 7 |
| 29. Number of Startups Funded* | 8 |
| 30. Number of funded startups per capita | 6 |
| **Robot Installations** | |
| 31. Robot Installations (in thousands of units) | 4 |

## Inclusion

| Gender Diversity | Scaled (0-100) |
|---|---|
| 32. Proportion of female AI authors | 62 |
| 33. AI Skill Penetration (female) | 35 |
| 34. Number of unique AI occupations | 22 |

[National_Strategies_AI_Vibrancy_Technical_Appendix]
[Access_Data]

## Country Profile: Germany

**2017.** The Federal Ministry of Education and Research launched a government aid campaign in the field of machine learning. Subsequently, it funded The Platform Learning Systems (an expert AI platform running from 2017 to 2022) and the Automated and Networked Driving Project. The Federal Ministry of Transport and Digital Infrastructure also published "Ethics Commission: Automated and Connected Driving," with 20 ethical guidelines for self-driving cars.

**November 2018.** Germany launched its Artificial Intelligence Strategy and allocated €3B for investment in AI R&D. The strategy was developed by the Economic Affairs Ministry, the Research Ministry, and the Labour Ministry. The strategy focuses on three objectives: (1) making Germany and Europe global leaders in AI; (2) developing AI which serves the good of society; (3) integrating AI into society in the active political context.

Previously, the German Institute for Innovation and Technology within the Federal Ministry for Economic Affairs and Energy found that AI will add approximately €32 billion to Germany's manufacturing output over the next five years.

# Germany

## Research and Development

| Conference Publications | Scaled (0-100) |
|---|---|
| 1. Number of AI conference papers* | 18 |
| 2. Number of AI conference papers per capita | 23 |
| 3. Number of AI conference citations* | 2 |
| 4. Number of AI conference citations per capita | 2 |
| 5. Number of AI conference references* | 16 |
| 6. Number of AI conference references per capita | 15 |
| **Journal Publications** | |
| 7. Number of AI journal papers* | 13 |
| 8. Number of AI journal papers per capita | 26 |
| 9. Number of AI journal citations* | 4 |
| 10. Number of AI journal citations per capita | 2 |
| 11. Number of AI journal references* | 17 |
| 12. Number of AI journal references per capita | 17 |
| **Innovation > Patents** | |
| 13. Number of AI patents* | 9 |
| 14. Number of AI patents per capita | 4 |
| 15. Number of AI patent citations* | 1 |
| 16. Number of AI patent citations per capita | 1 |
| 17. Number of AI patent references* | 1 |
| 18. Number of AI patent references per capita | 2 |
| **Journal Publications > Deep Learning** | |
| 19. Number of Deep Learning papers* | 16 |
| 20. Number of Deep Learning papers per capita | 17 |
| 21. Revealed Comparative Advantage (RCA) of Deep Learning Papers on arXiv | 26 |

## Economy

| Skills | Scaled (0-100) |
|---|---|
| 22. Percentile Rank of AI Skills on Coursera | 95 |
| 23. AI (% of total enrollment) | 53 |
| 24. Relative Skill Penetration | NA |
| 25. Number of unique AI occupations (job titles) | NA |
| **Labor** | |
| 26. AI hiring index | 59 |
| **Investment** | |
| 27. Total Amount of Funding* | 2 |
| 28. Total per capita Funding | 3 |
| 29. Number of Startups Funded* | 4 |
| 30. Number of funded startups per capita | 2 |
| **Robot Installations** | |
| 31. Robot Installations (in thousands of units) | 17 |

## Inclusion

| Gender Diversity | Scaled (0-100) |
|---|---|
| 32. Proportion of female AI authors | 49 |
| 33. AI Skill Penetration (female) | NA |
| 34. Number of unique AI occupations | NA |

[National_Strategies_AI_Vibrancy_Technical_Appendix]
[Access_Data]

## Country Profile: India

- **February 2018**. A Task Force was assigned by MoD to study the strategic implementation of AI for National Security and Defense.

- **June 2018**. The Indian government's think-tank NITI Aayog defined a national policy on AI in a working paper titled National Strategy for AI (#AIforAll). India has taken a unique approach to its national AI strategy by focusing on how it can leverage AI not only for economic growth, but also for social inclusion. The strategy aims to (1) enhance and empower Indians with the skills to find quality jobs, (2) invest in research and sectors that can maximize economic growth and social impact, and (3) scale Indian-made AI solutions to the rest of the developing world. The government wants to establish India as an "AI Garage," meaning that if a company can deploy an AI in India, it will then be applicable to the rest of the developing world.

  The strategy clarifies five major sectors that AI research in India will focus on – healthcare, agriculture, education, smart cities and infrastructure, and smart mobility and transportation. To pave the way for these advancements, the Indian government has doubled its allocation to the 'Digital India' program to $480m (₹3,073 crore) in 2018-19.

# India

## Research and Development

| Conference Publications | Scaled (0-100) |
|---|---|
| 1. Number of AI conference papers* | 20 |
| 2. Number of AI conference papers per capita | 2 |
| 3. Number of AI conference citations* | 1 |
| 4. Number of AI conference citations per capita | 0 |
| 5. Number of AI conference references* | 13 |
| 6. Number of AI conference references per capita | 1 |
| **Journal Publications** | |
| 7. Number of AI journal papers* | 28 |
| 8. Number of AI journal papers per capita | 3 |
| 9. Number of AI journal citations* | 5 |
| 10. Number of AI journal citations per capita | 0 |
| 11. Number of AI journal references* | 19 |
| 12. Number of AI journal references per capita | 1 |
| **Innovation > Patents** | |
| 13. Number of AI patents* | 1 |
| 14. Number of AI patents per capita | 0 |
| 15. Number of AI patent citations* | 0 |
| 16. Number of AI patent citations per capita | 0 |
| 17. Number of AI patent references* | 0 |
| 18. Number of AI patent references per capita | 0 |
| **Journal Publications > Deep Learning** | |
| 19. Number of Deep Learning papers* | 6 |
| 20. Number of Deep Learning papers per capita | 0 |
| 21. Revealed Comparative Advantage (RCA) of Deep Learning Papers on arXiv | 31 |

## Economy

| Skills | Scaled (0-100) |
|---|---|
| 22. Percentile Rank of AI Skills on Coursera | 41 |
| 23. AI (% of total enrollment) | 50 |
| 24. Relative Skill Penetration | 100 |
| 25. Number of unique AI occupations (job titles) | 99 |
| **Labor** | |
| 26. AI hiring index | 73 |
| **Investment** | |
| 27. Total Amount of Funding* | 1 |
| 28. Total per capita Funding | 0 |
| 29. Number of Startups Funded* | 5 |
| 30. Number of funded startups per capita | 0 |
| **Robot Installations** | |
| 31. Robot Installations (in thousands of units) | 3 |

## Inclusion

| Gender Diversity | Scaled (0-100) |
|---|---|
| 32. Proportion of female AI authors | 54 |
| 33. AI Skill Penetration (female) | 100 |
| 34. Number of unique AI occupations | 100 |

[National_Strategies_AI_Vibrancy_Technical_Appendix]
[Access_Data]

## Country Profile: The Netherlands

In **2018**, AINED*, the public-private partnership on AI, has formulated AI Voor Nederland — a first draft for a Dutch National AI strategy. The setup will provide a concrete action plan to make AI a national priority, with the Netherlands seeing potential for AI development in the areas of health, agriculture, mobility, and decarbonization. AINED is currently working in a public-private context to turn the report into a concrete action plan, which should be launched soon.

The report includes a wide range of measures that governments and businesses can take to help the Netherlands further its excellent standing in this field, and provides an interesting focus on education. A shortage of talent, for instance, can be obviated by making it easier for international students to extend their stay in the Netherlands after graduating. The Netherlands could also improve its collaboration in existing chains, develop a national AI research centre of high repute, serve as a catalyst for new businesses, and make better use of available data. Universities are already conducting good technical research; for instance, the University of Amsterdam collaborating with the municipality and other businesses to create Amsterdam's AI Hub.

The central government is, partly in response to the AINED report, also preparing an action plan.

*AINED was founded to map the position of the Netherlands in AI development and is a public-private partnership between TopTeam ICT, Dutch employer federation VNO-NCW, business group MKB Nederland, Innovation Center for Artificial Intelligence, Netherlands Organisation for Scientific Research (NWO) and Netherlands Organisation for Applied Scientific Research (TNO).

# The Netherlands

## Research and Development

| Conference Publications | Scaled (0-100) |
|---|---|
| 1. Number of AI conference papers* | 4 |
| 2. Number of AI conference papers per capita | 22 |
| 3. Number of AI conference citations* | 1 |
| 4. Number of AI conference citations per capita | 3 |
| 5. Number of AI conference references* | 4 |
| 6. Number of AI conference references per capita | 17 |
| **Journal Publications** | |
| 7. Number of AI journal papers* | 5 |
| 8. Number of AI journal papers per capita | 47 |
| 9. Number of AI journal citations* | 2 |
| 10. Number of AI journal citations per capita | 5 |
| 11. Number of AI journal references* | 7 |
| 12. Number of AI journal references per capita | 34 |
| **Innovation > Patents** | |
| 13. Number of AI patents* | 0 |
| 14. Number of AI patents per capita | 1 |
| 15. Number of AI patent citations* | NA |
| 16. Number of AI patent citations per capita | NA |
| 17. Number of AI patent references* | 0 |
| 18. Number of AI patent references per capita | 0 |
| **Journal Publications > Deep Learning** | |
| 19. Number of Deep Learning papers* | 5 |
| 20. Number of Deep Learning papers per capita | 23 |
| 21. Revealed Comparative Advantage (RCA) of Deep Learning Papers on arXiv | 29 |

## Economy

| Skills | Scaled (0-100) |
|---|---|
| 22. Percentile Rank of AI Skills on Coursera | 86 |
| 23. AI (% of total enrollment) | 42 |
| 24. Relative Skill Penetration | 23 |
| 25. Number of unique AI occupations (job titles) | 13 |
| **Labor** | |
| 26. AI hiring index | 62 |
| **Investment** | |
| 27. Total Amount of Funding* | 0 |
| 28. Total per capita Funding | 2 |
| 29. Number of Startups Funded* | 1 |
| 30. Number of funded startups per capita | 4 |
| **Robot Installations** | NA |
| 31. Robot Installations (in thousands of units) | |

## Inclusion

| Gender Diversity | Scaled (0-100) |
|---|---|
| 32. Proportion of female AI authors | 82 |
| 33. AI Skill Penetration (female) | 42 |
| 34. Number of unique AI occupations | 7 |

[National_Strategies_AI_Vibrancy_Technical_Appendix]
[Access_Data]

## Country Profile: Singapore

AI has been identified as one of four frontier technologies which are essential to growing Singapore's economy. Singapore aims to advance its vision to be a leading Digital Economy and Smart Nation, continually embracing digital transformation and reinventing itself to remain globally competitive. In doing so, Singapore focuses on the technical capabilities, technology investments, and regulatory requirements through the following core initiatives:

**May 2017.** The Singaporean government launched AI Singapore (AISG) with $150 million in funding to catalyse, synergise and boost Singapore's AI capabilities. Today, AISG is Singapore's premier national research and innovation programme in AI.

**2018.** The Singaporean government established an Advisory Council on the Ethical Use of AI and Data, an industry-led initiative to examine legal and ethical issues raised by commercial deployment of AI. Members comprise international leaders in AI such as Google, Microsoft and Alibaba. The Research Programme on the Governance of AI and Data was also set up with the Singapore Management University.

**November 2019.** Singapore's National AI Strategy (NAIS) was unveiled by the Deputy Prime Minister. The full NAIS is available publicly.

**Davos 2019**. At Davos the Singaporean government announced it is working with the World Economic Forum's Centre for Fourth Industrial Revolution (WEF C4IR) to help drive the ethical and responsible deployment of artificially intelligent technologies. Singapore's Model AI Governance Framework is the first of its kind to exist throughout Asia and provides detailed guidance to private sector organizations to address key ethical and governance issues when building, deploying and investing in AI solutions. Singapore has long been pushing to become a global leader in AI, and this Model Framework will be welcomed by those who work with this emerging technology.

# Singapore

## Research and Development

| Conference Publications | Scaled (0-100) |
| --- | --- |
| 1. Number of AI conference papers* | 5 |
| 2. Number of AI conference papers per capita | 87 |
| 3. Number of AI conference citations* | 1 |
| 4. Number of AI conference citations per capita | 19 |
| 5. Number of AI conference references* | 7 |
| 6. Number of AI conference references per capita | 92 |
| **Journal Publications** | |
| 7. Number of AI journal papers* | 3 |
| 8. Number of AI journal papers per capita | 100 |
| 9. Number of AI journal citations* | 3 |
| 10. Number of AI journal citations per capita | 20 |
| 11. Number of AI journal references* | 7 |
| 12. Number of AI journal references per capita | 100 |
| **Innovation > Patents** | |
| 13. Number of AI patents* | 1 |
| 14. Number of AI patents per capita | 4 |
| 15. Number of AI patent citations* | NA |
| 16. Number of AI patent citations per capita | NA |
| 17. Number of AI patent references* | 0 |
| 18. Number of AI patent references per capita | 2 |
| **Journal Publications > Deep Learning** | |
| 19. Number of Deep Learning papers* | 6 |
| 20. Number of Deep Learning papers per capita | 100 |
| 21. Revealed Comparative Advantage (RCA) of Deep Learning Papers on arXiv | 39 |

## Economy

| Skills | Scaled (0-100) |
| --- | --- |
| 22. Percentile Rank of AI Skills on Coursera | 93 |
| 23. AI (% of total enrollment) | 34 |
| 24. Relative Skill Penetration | 32 |
| 25. Number of unique AI occupations (job titles) | 11 |
| **Labor** | |
| 26. AI hiring index | 100 |
| **Investment** | |
| 27. Total Amount of Funding* | 3 |
| 28. Total per capita Funding | 65 |
| 29. Number of Startups Funded* | 3 |
| 30. Number of funded startups per capita | 26 |
| **Robot Installations** | |
| 31. Robot Installations (in thousands of units) | 3 |

## Inclusion

| Gender Diversity | Scaled (0-100) |
| --- | --- |
| 32. Proportion of female AI authors | 33 |
| 33. AI Skill Penetration (female) | 27 |
| 34. Number of unique AI occupations | 9 |

[National_Strategies_AI_Vibrancy_Technical_Appendix]
[Access_Data]

## Country Profile: The United States

**February 2019. Launch of the American AI Initiative**
In February 2019, the President signed an Executive Order launching the American AI Initiative, which will take a multipronged approach to accelerating America's national leadership in AI. The Executive Order states that the Federal Government will have a central role not only in facilitating AI R&D, but also in promoting trust, training people for a changing workforce, protecting national security, enhancing collaboration with foreign partners and the private sector.

**June 2019. Launch of the US AI R&D Strategic Plan**
In June 2019, the White House's AI R&D Strategic Plan defines several key areas of priority focus for the Federal agencies that invest in AI. These areas of strategic AI R&D focus include: (1) continued long-term investments in AI (2) effective methods for human-AI collaboration (3) understanding and addressing the ethical, legal, and societal implications for AI (4) ensuring the safety and security of AI (5) developing shared public datasets and environments for AI training and testing (6) measuring and evaluating AI technologies through standards and benchmark (7) better understanding the National AI R&D workforce needs, and (8) expanding public-private partnerships to accelerate AI advances.

2019 marked the biggest year in funding, both federal and private, for artificial intelligence ventures yet. For 2020, the President's Budget prioritizes AI as one of four key Industries of the Future to invest in. Annual federal spending on non-defence-related AI research is set to jump to nearly $1 billion. That figure represents an increase, given that agencies including the US defence department and non-defence related entities spent about US$1 billion on AI research in 2016.

**September 2018.** DARPA announced the "AI Next" campaign, a multi-year investment $2b+ in new and existing programs. Key areas of the campaign include automating critical DoD business processes. AI Next builds on DARPA's five decades of AI technology creation to define and to shape the future, always with the Department's hardest problems in mind.

**October 2019.** The Defense Innovation Board, a panel of 16 prominent technologists advising the Pentagon, voted to approve AI ethics principles for the Department of Defense. The report includes 12 recommendations for how the US military can apply ethics in the future for both combat and non-combat AI systems.

**November 2019.** The interim report was released by the National Security Commission on AI.

# The United States

## Research and Development

| Conference Publications | Scaled (0-100) |
|---|---|
| 1. Number of AI conference papers* | 100 |
| 2. Number of AI conference papers per capita | 33 |
| 3. Number of AI conference citations* | 21 |
| 4. Number of AI conference citations per capita | 6 |
| 5. Number of AI conference references* | 100 |
| 6. Number of AI conference references per capita | 24 |
| **Journal Publications** | |
| 7. Number of AI journal papers* | 80 |
| 8. Number of AI journal papers per capita | 40 |
| 9. Number of AI journal citations* | 29 |
| 10. Number of AI journal citations per capita | 3 |
| 11. Number of AI journal references* | 88 |
| 12. Number of AI journal references per capita | 23 |
| **Innovation > Patents** | |
| 13. Number of AI patents* | 84 |
| 14. Number of AI patents per capita | 9 |
| 15. Number of AI patent citations* | 5 |
| 16. Number of AI patent citations per capita | 2 |
| 17. Number of AI patent references* | 18 |
| 18. Number of AI patent references per capita | 8 |
| **Journal Publications > Deep Learning** | |
| 19. Number of Deep Learning papers* | 100 |
| 20. Number of Deep Learning papers per capita | 27 |
| 21. Revealed Comparative Advantage (RCA) of Deep Learning Papers on arXiv | 32 |

## Economy

| Skills | Scaled (0-100) |
|---|---|
| 22. Percentile Rank of AI Skills on Coursera | 81 |
| 23. AI (% of total enrollment) | 65 |
| 24. Relative Skill Penetration | 76 |
| 25. Number of unique AI occupations (job titles) | 100 |
| **Labor** | |
| 26. AI hiring index | 65 |
| **Investment** | |
| 27. Total Amount of Funding* | 100 |
| 28. Total per capita Funding | 37 |
| 29. Number of Startups Funded* | 100 |
| 30. Number of funded startups per capita | 14 |
| **Robot Installations** | |
| 31. Robot Installations (in thousands of units) | 26 |

## Inclusion

| Gender Diversity | Scaled (0-100) |
|---|---|
| 32. Proportion of female AI authors | 53 |
| 33. AI Skill Penetration (female) | 60 |
| 34. Number of unique AI occupations | 82 |

[National_Strategies_AI_Vibrancy_Technical_Appendix]
[Access_Data]

## Multilateral and Regional AI Policy

United Nations Activity on Artificial Intelligence is a joint-effort between ITU and 32 UN agencies and bodies, all partners of 2018's AI for Good Global Summit, this report provides information about the diverse and innovative activities related to artificial intelligence (AI) across the UN system.

The WTO foresees that AI will transform the administration of the world trading system. While the world trading system will continue to be tested, they foresee that it will endure and improvements will be made to make it effective with respect to all aspects of global need.

In 2019 presentation Multilateral Trading System and WTO Reform: Making Globalization Serve Society, Joseph Stiglitz argues that as we reform the WTO—to strengthen the rules-based multilateral system—we need to keep paramount that trade is not an end in itself but a means to an end, enhancing the well-being of all citizens of the world.

The High-Level Expert Group on Artificial Intelligence (AI HLEG) has as a general objective to support the implementation of the European Strategy on Artificial Intelligence. HLEG has also released the Ethics Guidelines for Trustworthy AI.

The European AI Alliance constitutes a key forum engaged in a broad and open discussion of all aspects of Artificial Intelligence development and its impacts.

In May 2019, Forty-two countries adopted new OECD Principles on Artificial Intelligence, agreeing to uphold international standards that aim to ensure AI systems are designed to be robust, safe, fair and trustworthy.

OECD Global AI Observatory provides evidence and guidance on AI metrics, policies and practices, facilitating dialogue and sharing best practices on AI policies.

OECD Principles on Artificial Intelligence complements existing OECD standards in areas such as privacy, digital security risk management, and responsible business conduct in the context of AI. The book OECD Artificial Intelligence in Society delineates a plan for implementing the Principles in practice. The OECD Private Equity Investment in Artificial Intelligence shows important increases in investments in AI startups. In 2020, they will release the OECD AI Policy Observatory.