THE OBSERVER

The Global AI Index

Methodology Report

December 2025

Overview

Launched in 2019, the Global AI Index (GAII) was the first to rank countries based on capacity for artificial intelligence, by measuring levels of investment, innovation and implementation. For the sixth iteration of the index, The Observer has worked to further reflect the current international landscape across the areas of talent, infrastructure, operating environment, research, development, commercial ecosystem and government strategy.

This report details the underlying methodology of the Global AI Index, including the rationale for its structure and the techniques behind the data collection, imputation, weighting and scoring. As a composite index, the GAII draws on 23 different data sources, including government reports, public databases from international organisations, think-tanks and private companies, as well as The Observer's own research, to measure the national ecosystems that determine capacity for artificial intelligence.

The 108 indicators that comprise the Global AI Index have been selected because they:

- Reflect publicly-available information;
- Use up-to-date data sources;
- Relate to key developments in the artificial intelligence sector.

The indicators are grouped by associative themes around three main pillars and seven sub-pillars:

- **Implementation**. Indicators within this pillar reflect the availability of institutions, systems and practitioners needed to operationalise artificial intelligence in business, government and communities. This pillar contains the sub-pillars of talent, infrastructure and operating environment.
- **Innovation**. Indicators within this pillar reflect breakthroughs in technology that are indicative of greater capacity for artificial intelligence in the future. This pillar contains the sub-pillars of research and development.
- **Investment.** Indicators within this pillar reflect financial and procedural investments in artificial intelligence. This pillar contains the sub-pillars of commercial ecosystem and government strategy.

Why measure AI capacity?

Artificial intelligence holds enormous power to transform business, government and society. Measuring countries' AI capacity – from computing infrastructure access to cutting-edge technology development, talent availability and capital investment – means understanding the extent to which they are set to harness such power.

Capacity – the amount of something that a system can contain or produce – is the organising concept of the Global AI Index. It is an appropriate means of considering the relationship between the different relevant factors that co-exist within a given nation. Capacity for artificial intelligence expresses both the breadth and depth of adoption, as well as improvements in a given nation's ability to manage and sustain artificial intelligence systems now and in the future.

Within the Global AI Index, capacity is measured through composite indicators which – through aggregation – consolidate a large amount of data into a set of simplified numbers that reflect the underlying complexity of information.

Guiding principles

The key methodological principles that underpin the indicators used in the Global AI Index are detailed below:

1. **Relevance.** Each of our variables speak to a contemporary aspect of the field of artificial intelligence. For example, 'Contributions to top models represented in the LMarena leaderboard' is a factor that features regularly in contemporary discussion.

2. **Relatability.** Our selected variables are to be accessible to specialists and non-specialists alike, phrased in clear terms. This accessibility makes the index more transparent, allowing users to question inclusions and the relationships that they show.

3. **Sizable contribution.** Our indicators provide a substantial contribution to a country's overall level of capacity.For example, the 'Number of AI Research Scientists' is widely regarded as relevant in contributing to a nation's capacity.

The Global AI Index includes mainly quantitative data (e.g. the number of AI research scientists, startups or GPU clusters). In a small number of cases, qualitative data is included (e.g. response data from the IPSOS survey question "Products and services using artificial intelligence make me excited") and is packaged as quantitative for comparability purposes.

Pillars and sub-pillars

This section shows the organisation of the sub-pillars and offers a justification for their inclusion in the Global AI Index, along with their constituent indicators. These justifications reflect our understanding of the interrelated factors that contribute to capacity on a national scale. The fast-changing and ever-shifting processes of innovation and implementation in artificial intelligence require constant re-examination of individual indicators, but these pillars and sub-pillars have remained consistent across multiple iterations of the index from its inception.

Implementation | Talent

Artificial intelligence is implemented by people. This refers to the practitioners of artificial intelligence who are employed by the public and private sector to apply technology to specific problems. Capacity, therefore, is based substantially on the personnel able to deploy, implement and manage technology systems.
The geographical concentration of AI specialists and developers, their career level, as well as the changing supply and demand for them across industry sectors, is the focus of the 'Talent' sub-pillar. The purpose of measuring talent is to define the level of capacity offered by human capital within a given nation.

Implementation | Infrastructure

Reliable digital infrastructure, computing capabilities and chip manufacturing are required to sustain the operationalisation of different artificial intelligence solutions and increase AI adoption.

Today, measuring infrastructure involves looking at the availability of high-performance computing resources, and the ability to manufacture or acquire advanced semiconductors.

Implementation | Operating Environment

In order for technological development to progress, there must exist a conducive wider environment for invention. In the Global AI Index, the operating environment stands for the institutional, economic and cultural factors that significantly affect the application of AI technologies.

The 'Operating Environment' sub-pillar focuses on survey data indicating public attitudes towards artificial intelligence, the level of adoption of popular AI platforms by consumers and the overall quality of governance and institutions at the national level.

Innovation | Research

Research generates new ideas in artificial intelligence. Capacity as a result of innovation is substantially based upon the level of activity amongst research communities in both academia and industry, and the extent to which they share ideas.

Measuring the level of research includes an assessment of the volume and impact of AI research publications, attendance at established AI research conferences, the quality of education institutions, contributions to novel architectures and techniques in producing cutting edge AI models. The 'Research' sub-pillar is indicative of the advances in capability that contribute to capacity through new innovations.

Innovation | Development

While research is focused on generating and expanding knowledge, development involves the application of that knowledge in creating new AI products and capabilities.

The 'Development' sub-pillar focuses on the evolution of new AI models, primarily at the open-source level, the availability of datasets, and the application of AI technology in patents across other fields.

Investment | Commercial Ecosystem

Commercial ventures – businesses that are providing goods and services through a combination of financial and industrial avenues – are responsible for a large proportion of AI implementation around the world. The scale, funding and volume of these businesses is a contributor to capacity.

The increases in productivity, efficiency and reliability that machine learning can provide are all significant enhancements to cross-sectoral business performances. The 'Commercial Ecosystem' sub-pillar is focused on the industrial environment surrounding artificial intelligence in a given country, and involves analysing the number, scale, acquisitions and funding of AI companies.

Investment | Government Strategy

Government strategies – typically publications outlining approaches to digital transformation, innovation and artificial intelligence – provide detailed investment commitments across pillars of R&D, talent, infrastructure and business development.

The 'Government Strategy' sub-pillar evaluates the comprehensiveness, timeliness, and degree of ambition of countries' national AI strategies. Additionally, it measures government spending commitments towards AI in the areas of infrastructure, research, training and private sector support.

Calculating the Index

Geographical scope

The rapid transformation of public and private sector activities by artificial intelligence is a global phenomenon. With the aim of including as many nations as possible whilst maintaining the robustness and relevance of the underlying dataset, the sixth edition of the index includes 93 countries.

These are:

> Algeria, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Belgium, Benin, Brazil, Bulgaria, Cambodia, Canada, Chile, China, Colombia, Costa Rica, Côte d'Ivoire, Croatia, Czech Republic, Denmark, Dominican Republic, Egypt, Estonia, Ethiopia, Finland, France, Germany, Ghana, Greece, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Japan, Jordan, Kenya, Kuwait, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mauritius, Mexico, Morocco, Nepal, New Zealand, Nigeria, Norway, Oman, Pakistan, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Serbia, Sierra Leone, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tajikistan, Thailand, The Netherlands, Tunisia, Türkiye, Ukraine, United Arab Emirates, United Kingdom, United States of America, Uruguay, Uzbekistan, Vietnam, Zambia.

This list of included nations has been validated through a combination of discussions with industry experts, as well as a thorough literature review. Beginning with countries that published national AI strategies provided a basis for selecting countries with sufficient data available for ranking.

Temporal scope

Data currency is a leading priority of the Global AI Index. As such, the enforced temporal scope for data collection spans 2020 to the present day. Where updated values are unavailable, historical data is carried forward, with a cutoff of 2020 to ensure relevance.

For some indicators, a snapshot of the data in its most up-to-date state (e.g. the most capable models currently represented in the OpenLLM benchmark leaderboard) is taken. For other indicators, we aggregate across a five-year window, going back from the year of the most recent index.

The current sixth edition of the index therefore measures output from 2020 to 2025, disregarding data predating this period.

Scoring and weighting

A country's total score is made up of the weighted sum of its sub-pillar scores, which in turn are the weighted sum of indicator 'categories' within each sub-pillar. Thus, the overall category score is driven by each indicator.

This allows us to compare indicators within a given sub-pillar or category, such as Talent, rather than comparing all individual indicators separately. In the final presentation of the index, the overall score and the score for each sub-pillar are normalised between 100 and the minimum original score. We do not normalise the minimum score to 0, in order to avoid the impression from a 0 score that no AI activity is taking place at all.

The table below shows the weighting for each category. When added together, these produce the following overall sub-pillar weights:

Talent – 11%
Operating Environment – 8%
Infrastructure – 16%
Research – 17%
Development – 18%
Government Strategy – 12%
Commercial Ecosystem – 18%

And the following overall pillar weights:

Implementation - 35%
Innovation – 35%
Investment – 30%

Indicator categories

Pillar	Sub Pillar	Category	Category Weight
Implementation	Infrastructure	High-performance computing	7.00%
Implementation	Infrastructure	Semiconductor capacity	3.00%
Implementation	Infrastructure	Digital connectivity	2.00%
Implementation	Infrastructure	Electricity capacity	4.00%
Implementation	Talent	AI software developers	5.00%
Implementation	Talent	AI research scientists	5.00%
Implementation	Talent	AI professionals	1.00%

Implementation	Operating Environment	Public attitudes towards AI	3.00%
Implementation	Operating Environment	Public use	3.00%
Implementation	Operating Environment	Institutions and governance	2.00%
Investment	Government Strategy	Commercial strategy	2.00%
Investment	Government Strategy	Strategy governance	2.00%
Investment	Government Strategy	Infrastructure strategy	3.00%
Investment	Government Strategy	Research strategy	3.00%
Investment	Government Strategy	Training strategy	2.00%
Investment	Commercial	AI startups	7.00%
Investment	Commercial	AI private capital	9.00%
Investment	Commercial	AI company acquisitions	2.00%
Innovation	Research	R&D spenCd	2.00%
Innovation	Research	Model research	6.00%
Innovation	Research	Academic publications	4.00%
Innovation	Research	AI academic conferences	3.00%
Innovation	Research	Educational institutions	2.00%
Innovation	Development	Open-source models	6.00%
Innovation	Development	Open-source datasets	4.00%
Innovation	Development	AI patent activity	4.00%
Innovation	Development	Model leaderboards	4.00%

Each individual indicator is given a 'base weight' that determines how much it will contribute to the overall category in which it sits. This base weight is calculated according to three specific considerations: **1) relevance** to artificial intelligence, **2) contribution** to artificial intelligence capacity, and **3) reliability** of data.

For each consideration, we score the indicator between 1 and 5. These three considerations are then summed to reach a final 'base weight' between 3 and 15.

Weighting for relevance

Each indicator has been considered according to its relevance to the investment, innovation and implementation specific to artificial intelligence. Whilst we maintain that all inclusions in the index can be justified by this relevance, differences in relation between indices are reflected through their weighting.

Our assessment of relevance is based on the apparent connections between the indicator itself, and its influence on artificial intelligence capacity. For example, we consider 'Number of AI Research Scientists' to be a highly relevant capacity contributor and therefore, the indicator is heavily weighted in the 'Talent' sub-pillar of the index. Whilst 'Proportion of Population with Access to Electricity' is similarly connected to capacity, we consider it a less relevant factor. As a result, it is less heavily weighted in the 'Infrastructure' sub-pillar of the index.

Weighting for contribution

Each indicator has also been considered according to its contribution to overall capacity through investment, innovation and implementation. For example, 'Total electricity capacity in GW"' is considered a leading contributor to capacity (even if not specific to AI as an indicator) and this is reflected in a high indicator weighting. Contrastingly, 'Exports of Integrated Circuits as a proportion of GDP' is important but provides a less significant contribution to capacity and thus receives a lower weighting.

Weighting for reliability

Lastly, the reliability (comprehensiveness or quality) of data underpinning each indicator is included in the weighting system. This is to account for a range of potential quality issues including data completeness, availability, accessibility, reliability, precision and accuracy. Any compromises to our high standards of data quality result in a reduction of an indicator's relevant weight, in turn ensuring that data we feel confident in is weighted generously.

Weighting for scale and intensity

Once we have calculated the base weight, for the majority of indicators, we take two types of measurements: one based on total or 'absolute' output which contributes to 'AI scale', and one based on output relative to the country's population or economy size, which contributes to 'AI intensity'. We weight each 'relative' indicator at ⅓ the weight of its associated absolute indicators. The overall index is therefore broadly weighted 75 per cent for AI scale and 25 per cent for AI intensity.

Methodology updates for 2025

The past year has been transformative for artificial intelligence. Greater government activity, large-scale capital investment in computing infrastructure and concentrations of talent and resources in research labs have become increasingly central to national AI capacity.

This year, several new indicators have been introduced, based on newly-available datasets, whilst previous indicators that now lack relevancy or reliability in the contemporary AI landscape have been removed. Meanwhile, many existing indicators have been updated and changed to ensure they continue to capture the growing AI ecosystem accurately.

We have retained the overall pillar and sub-pillar framework, and the underlying weighting and scoring methodology of the index. Additionally, the scope of what constitutes AI remains the same, which we define broadly as technology that enables computers and machines to simulate human intelligence, rather than a narrower definition that might only encompass generative AI, for example.

Below is a summary of significant updates from the fifth to the sixth edition of the index.

Geographic scope

We have included 12 new countries to reflect their government's recent efforts towards publishing a national AI strategy.

Temporal scope

We have updated the earliest data collection date cutoff for relevant indicators from 2019 to 2020, so the index continues to cover a 5-year period from the current date.

Sub-pillar focus

Within each sub-pillar, we have made the following overall changes:

Talent: We have increased the weighting of research scientist and GitHub developer-based indicators, while decreasing the weight of LinkedIn based indicators, as LinkedIn data is not uniformly representative of talent across all countries. We have removed indicators that used StackOverflow data as platform usage has significantly declined in recent years.

Infrastructure: We have added indicators related to GPU clusters, data centres, and electricity capacity/availability.

Operating Environment: We have:
- Updated and expanded indicators concerning public attitudes towards AI;
- Added indicators that measure public use and adoption of popular consumer-facing AI platforms;
- Added indicators that measure the overall quality of governance and institutions at the national level, replacing previous indicators which focused on membership of international agreements like the Open Data Charter, or indicators which looked at legislative activity around AI.

Government Strategy: We have significantly reworked this sub-pillar to track government strategic activity and planned investment in the key areas of research, infrastructure, training and private sector support, while removing some indicators related to strategy governance (e.g. 'Timescale of Dedicated AI Strategy') which are no longer relevant.

Commercial Ecosystem: Indicators specific to “AI startups” have been removed due to increasingly high statistical collinearity with broader ‘AI companies’ indicators. This better reflects the current reality of the private sector, where innovation is distributed across companies of all sizes rather than concentrated solely in early-stage ventures.

Research: We have removed the distinction between ‘foundational’ and ‘applied’ AI research in academic publications (which was increasingly difficult to distinguish between in the data). This has been replaced with indicators for all top academic publications – measured by citation count
– to distinguish between quantity and quality of output.

Development: We have:
Introduced new indicators that measure and compare performance of frontier AI models on popular benchmarks and model leaderboards such as LMArena;
Removed indicators related to granted (as opposed to filed) patents and patents by nationality of applicant (as opposed to inventor) due to high statistical collinearity with other patent indicators. These have been replaced by indicators that measure PCT patents (patents filed in multiple jurisdictions);
Added indicators measuring the adoption of open-source models and datasets, based on the number of models derived/trained from initial models and datasets. These replace the prior methodology of measuring model/dataset adoption by download count.

Sub-pillar weights: As a result of the above changes, we made the following overall updates to pillar weights:
Talent: decreased from 15 to 11 per cent;
Infrastructure: increased from 11 to 16 per cent;
Operating environment: increased from 4 to 8 per cent;
Research: decreased from 22 to 17 per cent;
Development: remained the same at 18 per cent;
Government strategy: increased from 7 to 12 per cent;
Commercial ecosystem: decreased from 22 to 18 per cent.

FAQs

Why have we built the Global AI Index?
The Observer is fundamentally committed to data-driven journalism, understanding and explaining complex processes in our editorial output. We are also responding to the need amongst policy-makers, journalists, business leaders and society for a more comprehensive tool for understanding these processes.
The Global AI Index is part of our broader investigation of artificial intelligence, recognising that it is one of the defining and most complex forces shaping our world today.

Why is it an index and not just a set of presentations of data?
Presentations of individual datasets can be informative and are a key part of our reporting, but a composite index allows us to transform and simplify complex, multi-dimensional data into a single analysis that allows readers to:
Understand the big picture of AI national capacity;
Benchmark countries against their peers to identify strengths and weaknesses in areas such as talent or infrastructure; and
Track progress over time as the global AI landscape evolves.
We see this journalistic intent as complementary to a further set of strengths of the index format, following a framework provided in the OECD review 'Composite Indicators – A review' by Michaela Saisana Group of Applied Statistics Joint Research Centre at the European Commission.
– To summarise complex or multi-dimensional issues;
– To place countries' performance at the centre of the policy arena;
– To offer a rounded assessment of countries' performance;
– To enable judgments to be made on countries' efficiency;
– To facilitate communication with ordinary citizens;
– To be used for benchmarking countries of best performance;
– To indicate which countries represent the priority for improvement efforts;
– To stimulate the search for better data and better analytical efforts;
– To set local priorities, and to seek out improvements along dimensions of performance where gains are most readily secured.

How did you select your metrics?
We selected our metrics through consultation with expert advisors, who helped us build an understanding of the development of artificial intelligence. Next, we conducted a careful investigation of available national strategies and datasets, highlighting the common features to derive a list of indicators. As such, our metrics are selected on a combined basis of relevance, significance and high-quality data availability.

How does it make sense to measure the level of capacity within a given nation when many of the factors involved are highly mobile and transnational?
The AI ecosystem is undoubtedly globalised, with researchers moving between countries and multinational corporations operating in multiple jurisdictions. No perfect method exists to isolate national contribution in a globalised, permeable world. In practice however, we employ specific methodological rules for different types of indicators to define 'national' capacity on a case-by-case basis. For example, our talent indicators generally track individuals where they are currently located, while our development indicators for models assign nationality based on the main headquarters of the institution responsible for development.

How do you ensure the index is statistically robust?
We use standard techniques to validate that the index is statistically robust and comprehensible. These include:
Multivariate analysis to check for indicators that either exhibit very high collinearity (> 0.92) with each other (i.e. they are measuring the same phenomenon and therefore double counting) or little to no correlation (< 0.2) with either other

indicators or the overall concept of AI capacity. These indicators were removed or their methodology changed if there was not a strong theoretical justification for their inclusion.
Sensitivity analysis to check that no indicators or categories had an outsized, disproportionate effect on the overall ranking due to the nature of the data. A 'leave-one-out' sensitivity analysis showed the index maintained a correlation of > 0.98 when any single indicator was removed and > 0.94 when any single category was removed.

Don't the weightings of the index define the rankings and make this a subjective exercise? Why not use data-driven or equal-weighting schemes instead?
The Global AI Index, like all composite indices, is at heart a subjective exercise. It reflects the editorial opinion – backed by data and expert consultation – of The Observer on what is important and worth evaluating in the current field of artificial intelligence. This subjectivity is embedded primarily in the index's conceptual framework (the definition of 'AI capacity') and the selection of indicators, rather than solely in the weighting scheme.
We have chosen to assign weights based on our value judgment at both the indicator and category levels for a number of reasons. Firstly, it improves transparency. We feel it is easier for readers to understand our explicit judgments on what drives AI capacity than to interpret abstract statistical derivations of weights. Secondly, it allows for quality control, enabling us to adjust weights to account for data comprehensiveness or reliability issues in specific datasets. Thirdly, it allows us to directly integrate domain expertise into the index structure.
While these weights are determined qualitatively, they are refined through quantitative analysis to address sensitivity and collinearity as set out above. The resulting weighting scheme is relatively balanced across the 108 indicators, and our analysis finds the overall ranking does not differ dramatically from how the index would appear under equal or various statistically-driven weighting schemes.

Why have the indicators and/or weights changed from last year? Doesn't updating the methodology like this make comparing between years difficult?
The methodology behind the Global AI Index tends to undergo more frequent revision than many other international composite indicators. This is primarily for two reasons.
First, what constitutes AI technology, and how it is produced and advanced, is constantly changing. The rise of generative AI systems from one experimental technique amongst many to the dominant mode of AI today, and the corresponding shift of research power from academia to the private sector, requires us to constantly reassess what we measure. As such, our updates facilitate the measurement of current, rather than historical capacity.
Secondly, there is increasingly little settled expert consensus on which factors will define AI capacity in the near future. This uncertainty directly impacts how we weigh specific indicators. For example, the weighting for 'GPU clusters' depends on factors such as:

- **Scaling laws:** will pretraining scaling continue to yield sizable performance gains or plateau?
- **Infrastructure bottlenecks:** will the primary constraint on future AI computing be chip availability/power or electricity capacity?
- **Model architecture:** will the market consolidate around massive proprietary frontier models or smaller, open-weight specialised systems?

We aim to balance diverging expert views in our indicator and weighting selection, reevaluating and updating our methodology accordingly as new evidence on the future direction of AI comes to light. Each annual iteration of the index therefore represents a snapshot of the state of AI at a specific moment in time.

Appendix I

Sources and definitions

1. Implementation

1.1. Talent

1.1.1 AI research scientists
Refers to the total number of top AI research scientists currently residing in a given country. 'Top' AI researchers are defined from a dataset of individuals sampled from two datasets:
The top contributors to papers (10,000 individuals) at leading academic AI conferences from 2020 to 2025, ranked by average citation weight of three most highly-cited accepted papers;
The top contributors to AI models (3,805 individuals) from 2020 to 2025, limited to those cited as contributing to at least two or more unique models.

Current affiliation and country location for each individual is collected through both AI assisted and manual searches across relevant academic and social network platforms (e.g. Google Scholar, OpenReview, GitHub, LinkedIn, personal websites).

Source: For models contributors, Epoch AI's "AI Model" database (https://epoch.ai/data/ai-models). For conference contributors, annual submissions to NeurIPS (https://neurips.cc), ICML (https://icml.cc), ICRA (https://2025.ieee-icra.org), ICLR (https://iclr.cc) and CVPR (https://cvpr.thecvf.com)

1.1.2 AI software developers
Refers to the number of developers contributing to open-source repositories tagged with an AI-related technical topic. GitHub labels repositories with topics, from which we have selected 75 AI-related ones based on technical fields or popular development frameworks (e.g. 'reinforcement-learning', 'huggingface') that capture the AI open-source ecosystem.

Source: GitHub Innovation Graph (https://innovationgraph.github.com)

1.1.3 AI professionals
Refers to the depth of AI skill penetration and talent concentration in a given country based on LinkedIn profile data (analysed by the OECD).

Source: LinkedIn via OECD AI Observatory (https://oecd.ai/en/data)

1.2. Infrastructure

1.2.1 High-performance computing
Defined as the number and total computational rate (in operating points/s) of large AI GPU clusters and supercomputers, and the number of large-scale data centres with >10MW capacity.

Source: For GPU clusters and supercomputers, Epoch AI's GPU cluster database (https://epoch.ai/data/gpu-clusters). For data centres, Data Center Map (https://www.datacentermap.com)

1.2.2 Electricity capacity
Refers to the total electrical capacity (GW) and total annual electricity generation (TWh) of a given country.

Source: Ember (https://ember-energy.org/)

1.2.3 Semiconductor capacity
Defined by the total import and export value (in USD) of 'integrated circuits' (HS 85.42) and 'machines and apparatus of a kind used solely or principally for the manufacture of semiconductor boules or wafers' (HS 84.86).

Source: The Observatory of Economic Complexity (https://oec.world/en)

1.2.4 Digital connectivity
Defined by the average monthly download speed and the proportion of total population with access to electricity.

Source: For download speed Speedtest (https://www.speedtest.net/). For internet access, World Bank (https://data.worldbank.org/indicator/IT.NET.USER.ZS)

1.3. Operating Environment

1.3.1 Public attitudes towards AI
Refers to various public survey responses on sentiment towards AI, including levels of nervousness versus excitement about AI products, benefits versus drawbacks of AI products, and expectations of profound change to daily life in the next 3 to 5 years as a result of AI.

Source: Ipsos AI Monitor 2025 Survey (https://www.ipsos.com/en-id/press-release-ipsos-ai-monitor-2025)

1.3.2 Public use
Refers to the level of use and adoption of popular AI consumer platforms and services (e.g. ChatGPT, Gemini, DeepSeek), based on traffic to websites and Microsoft telemetry on AI usage.

Source: For web traffic, Similarweb (https://similarweb.com). For usage, Microsoft AI Economy Institute (https://www.microsoft.com/en-us/research/group/aiei/ai-diffusion/)

1.3.3 Institutions and governance
Defined by a set of general governance quality indicators, including; government effectiveness', 'regulatory quality', 'rule of law' and 'policy stability'.

Source: Worldbank Worldwide Governance Indicators (https://www.worldbank.org/en/publication/worldwide-governance-indicators) and Travel & Tourism Development Index (TTDI) (https://data360.worldbank.org/en/indicator/WEF_TTDI_EOSQ434)

2. Innovation

2.1. Research

2.1.1 AI research conferences
Refers to author contribution towards submissions to popular AI research conferences, with separate indicators for a) all accepted submissions, and b) high-quality submissions chosen for highlight, spotlight, or oral presentation.

For research and development indicators that measure contribution to output 'items' (e.g. models, academic papers, patents) for which multiple authors or institutions of different nationality may have contributed to a single item, contribution is calculated as a proportional share based on authors. For example, a paper with one author from a British university, and three authors from a Chinese university would count as a 0.25 contribution towards the UK, and 0.75 towards China.

Source: Annual submissions to NeurIPS (https://neurips.cc), ICML (https://icml.cc), ICRA (https://2025.ieee-icra.org), ICLR (https://iclr.cc) and CVPR (https://cvpr.thecvf.com)

2.1.2 AI research publications
Refers to author contribution towards AI research publications, with separate indicators for a) all publications, and b) the top 1% most cited publications (by field weighted citation impact).

AI research publications are classified according to the computer science ontology (CSO) developed by the Knowledge Media Institute at the Open University. An initial dataset of papers is first collected from OpenAlex (any paper tagged with the 'Computer Science' field). Each paper is then classified using CSO, and the dataset filtered to include only papers that are tagged with one of 2000 AI-related subtopics.

Source: OpenAlex (https://openalex.org)

2.1.3 R&D spend
Refers to the overall (non AI-specific) annual research and development expenditure of a given nation, including capital and current expenditures in business enterprise, government, higher education and private non-profit. Covers basic research, applied research, and experimental development.

Source: World Bank (https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS)

2.1.4 Educational institutions
Defined as the number of universities that rank within the top 1000 of the Times Higher Education computer science league table for a given country.

Source: Times Higher Education (https://www.timeshighereducation.com/)

2.1.5 Model research
Defined as the contribution towards AI models, with separate indicators for a) any AI model and b) 'state-of-the-art' models (models that achieved contemporary state of the art performance on a recognised benchmark). Nationality based on the main location of the uploading organisations and institutions.

Source: Epoch AI's "AI Model" database (https://epoch.ai/data/ai-models)

2.2. Development

2.2.1 Open-source models
Defined as the contribution towards open-source/weight models uploaded to the HuggingFace platform. This is separated into indicators for a) number of models represented in the top 1000 models ranked by download count and b) number of models that are finetuned or otherwise derived from 'base models' within the top 1000 list of models.
Nationality based on the main location of the uploading organisation or individual, which was ascertained through both AI-assisted and manual searches on HuggingFace and other relevant social media platforms (GitHub, company websites etc).

Source: Huggingface (https://huggingface.co/models)

2.2.2 Open-source datasets
Defined as the contribution towards open-source datasets uploaded to the HuggingFace platform. This is separated into indicators for a) number of datasets represented in the top 1000 datasets ranked by download count and b) number of models that were trained from models within the top 1000 list of datasets. Nationality based on the main location of the uploading organisation or individual, which was ascertained through both AI-assisted and manual searches on HuggingFace and other relevant social media platforms (GitHub, company websites etc).

Source: Huggingface (https://huggingface.co/models)

2.2.3 Model leaderboards
Defined as the averaged score of the top three models on AI benchmark leaderboards for a given country. This includes LMarena (ELO score) and averages of benchmarks scores from GPQA Diamond, LiveCodeBench and Humanity's Last Exam.

Source: LMArena (https://lmarena.ai/), Artificial Analysis Leaderboards (https://artificialanalysis.ai/)

2.2.4 AI patent activity
Refers to contribution towards filed AI related patents. This is separated into indicators for a) the number of AI related patents filed under any jurisdiction, for mostly domestic applications), and b) the number of AI related patents filed under the Patent Cooperation Treaty (PCT), for international applications.

AI-related patents are identified using a combination of the World Intellectual Property Organisation's (WIPO) artificial intelligence query methodology and our own set of AI terminology keywords.

Source: IFI CLAIMS Patent Services (https://www.ificlaims.com/)

3. Investment

3.1. Government strategy

For government strategy indicators, we collected data on government AI expenditure and investment via desk research of official government sources (reports, publications and press releases) and then invited all involved national governments to review and make recommendations/amendments to our data via a right of reply process, as well as provide appropriate supporting evidence. We included or excluded spend data based on a set of criteria set out here: GAII 6.0 _ AI government spending methodology.pdf

3.1.1 Strategy governance
Defined as a set of 'checklist' indicators on how a given government is governing its national AI strategy. These checklists measure where a government has:
- A dedicated AI body;
- An up-to-date AI strategy report;
- A senior minister or secretary of state for AI; and
- Tracking mechanisms to measure progress on AI strategy.

Source: Official government documentation

3.1.2 Private sector support strategy
Refers to government commitments to support the private sector in AI development and adoption. This covers:
- Measurable targets to establish or support domestic AI startups;
- Measurable targets to support the adoption and use of AI within businesses; and
- Publicly announced investments or expenditure to support AI in the private sector.

Source: Official government documentation

3.1.3 Infrastructure strategy
Refers to government commitments to support the building and expansion of physical AI infrastructure. This covers:
- Measurable targets to create or expand new AI supercomputers/high-performance computing capacity;
- Measurable targets to expand and improve physical connectivity infrastructure; and
- Publicly announced investments or expenditure to support building out AI infrastructure.

Source: Official government documentation

3.1.4 Research strategy
Refers to government commitments to support AI research. This covers
- Measurable targets to create or expand new AI focused academic/higher education positions;
- Measurable targets to create or expand the new AI research hubs/clusters/centres of excellence; and
- Publicly announced investments or expenditure to support AI research.

Source: Official government documentation

3.1.5 Training strategy
Refers to government commitments to support AI training and upskilling of individuals. This covers
- Measurable targets to train or upskill individuals in the use of AI;
- Measurable targets to train or upskill individuals in the use of AI specifically within the education sector; and
- Publicly announced investments or expenditure to support AI training initiatives.

Source: Official government documentation

3.2. Commercial ecosystem

3.2.1 AI companies
Refers to the number of AI companies within a given country. This is separated into indicators for a) the number of any type of AI companies, and b) the number of AI companies listed on national stock exchanges.

AI companies are identified via Crunchbase's industry-based classification system for each company.

Source: Crunchbase (https://www.crunchbase.com/)

3.2.2 AI private investment

Refers to the amount of private investment being allocated to AI companies and the level of associated activity, with indicators for:

- Total private investment into AI companies in USD;
- Average size of funding round for AI companies in a given country;
- Number of AI-related funding rounds into AI companies in a given country.

AI private investment refers to external funding (equity and debt financing) from venture capital funds and corporate investors directed toward AI companies. It does not cover a company's internal capital expenditure on AI.

Source: Crunchbase (https://www.crunchbase.com/)

3.2.3 AI acquisitions

Refers to acquisition of AI startups by other companies, separated into indicators for the number of AI acquisitions and the total value in USD of those acquisitions. This tracks the nationality of the acquiring company rather than the acquired AI startup.

Source: Crunchbase (https://www.crunchbase.com/)