Using Online Labor Market Data to Measure AI Impact

Layla O'Kane, Director of Research, Lightcast

As artificial intelligence (AI) continues to reshape the way we live and work, measuring its size and impact in the economy will become increasingly important for policymakers, as well as for workers, learners, and employers who are trying to understand how to incorporate AI into their decision-making. This measurement challenge holds true for a wide range of emerging and important technologies, including green jobs, digital jobs,and other key areas of investment for a future-ready workforce. Real-time labor market data, such as online job postings and online social profile data, can help support this measurement challenge and provide insight into high-level growth trends as well as granular information on which occupations, geographies, and sectors have been most affected by AI. This paper outlines key variables available in these data, a working definition of AI using a "basket-of-skills" approach, challenges and opportunities with this methodology, and potential next steps and applications to other technologies.

Approaches to AI measurement using online labor market data

Two primary online labor market data sources are job postings data and social profile data. Job postings data comprise an aggregate of online job advertisements or job postings that are scraped from individual employer websites, government sources, job boards, and other aggregators with high frequency, often daily. Social profile data is sourced from online professional profiles and includes information similar to that of a resume or CV. More information on the information available in each of these data sources can be found in Table 1.

Table 1: Information Available From Online Labor Market Data

Information extracted from job posts	Information extracted from social profiles or resumes
• Employer name and industry/sector • Job title/occupation • Skill requirements, including AI technologies or AI-related skills • Education, certification, and experience requirements • Compensation • Job location • Job type: Full-time, part-time, permanent, temporary, internship, remote, etc. • Duration of post	• Worker name (generally anonymized during processing and aggregation) • Residential location and job locations • Current and former job titles/occupations • Time spent in each role • Current and former employers and industries • Skills and competencies, including AI-related skills or technologies • Certifications, degree attainment, and education programs

Source: Adapted from "Big Data for the Labor Market: Sources, Uses and Opportunities." APEC Policy Support Union. APEC Secretariat, December 2021. https://www.apec.org/docs/default-source/publications/2021/12/big-data-for-the-labor-market-sources-uses-and-opportunities/221_psu_big-data-for-the-labor-market.pdf?sfvrsn=e379d9be_2.

One of the main challenges for AI measurement is that AI does not reside only in one industry or occupation, but rather cuts across many sectors, employers, and types of jobs. However, both job posting data and social profile data can use skills and competencies, instead of sectors, to create a definition of AI. This makes for a flexible and dynamic measurement system that can look across the labor market. Specifically, one can define AI jobs as all jobs that require an AI-related skill (e.g. Natural Language Processing, Robotics, Autonomous Driving). This "basket-of-skills" approach allows for flexibility in the definition to account for:

- Distinguishing between developers of artificial intelligence tools and users of those tools. For example, this definition could include both a Software Engineer building a machine

learning model as well as a Curriculum Writer using ChatGPT to support their copyediting
- Direct technical skills (e.g. “Python”) and subject-matter expertise (e.g. “Computer Vision”)
- Sub-clusters of AI skills, such as Generative AI, Machine Learning, Visual Image Recognition, Robotics, Neural Networks, etc.

An example of the skills that could be included in an AI measurement definition can be found in the Appendix.

Using this approach can answer questions about the impact of a new policy change such as:

- Was there an increase in demand for AI jobs (total job postings)?
- Which occupations, locations, industries, or employers saw the biggest increase in demand for AI jobs or AI skills?
- Which AI skills were most demanded before and after the policy change?
- What new companies were created after the policy change that are focused on AI jobs?
- What job titles have had the highest growth in AI skills and what other skills frequently co-occur with these AI skills (e.g., leadership, management, collaboration, etc.)?
- What is the salary premium associated with certain AI skills and has that changed over time?
- Which certifications, majors, or education programs are demanded most by employers or do workers advertise having?

In addition to the granularity and flexibility that this measurement approach offers, there are also other advantages to using real-time online labor market data, especially when compared with more traditional methods of measurement such as survey data. These data, by nature, are real-time, which means you can capture new skills and technologies very quickly. In contrast, survey data is slow to collect and often has lags of at least one month if not longer. This allows for measurement to see emerging trends very quickly, especially with new technologies.

Similarly, due to the nature of “big data" sample sizes (upwards of 30M postings in the United States annually), sample size issues become less of a concern for measuring results relative to survey data. If a policy is implemented that targets only one or two new technologies, this effect can still be tracked.The data also makes for easy comparison across countries, industries, or other sub-sectors, especially if there is taxonomy alignment which is rare in publicly available survey data across countries.

This approach to AI measurement has already gained traction, with variations of this basket-of-skills approach have been taken in several recent publications on AI:

- The Stanford Institute for Human-Centered Artificial Intelligence annually publishes the *Stanford AI Index*[1], a report that uses this approach in the Economy chapter to highlight growth in AI job postings over time.
- The Organisation for Economic Cooperation and Development (OECD) and Lightcast joint report *Emerging Trends in AI Skill Demand Across 14 OECD Countries*[2] published in October 2023 showed an increase in demand for socio-emotional, foundational, and technical skills across AI employers and growth in AI in ICT and Professional Services across 14 OECD countries. This was followed by the *OECD Skills Outlook 2023*[3] which highlighted the need for ethical AI skills.
- A compendium of analysis published in 2022 by the European Network on Regional Labour Market Monitoring titled *The Relevance of Artificial Intelligence in the Digital and Green Transformation of Regional and Local Labour Markets across Europe*[4] showed the growth in AI in the labor market across large EU countries.
- In their 2022 paper *Artificial Intelligence and Jobs: Evidence from Online Vacancies*[5], Acemoglu et al. find that there is rapid growth in AI-related jobs and these are driven by firms who have workers with tasks compatible with current AI technologies.
- Goldfarb et al., in their 2020 paper *Artificial Intelligence in Health Care: Evidence from Online Job Postings,*[6] find that there has been relatively little adoption in the healthcare industry despite substantial media discussion of AI in healthcare.

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[1] "The AI Index 2023 Annual Report." AI Index Steering Committee. Stanford University, April 2023. https://aiindex.stanford.edu/wp-content/uploads/2023/04/HAI_AI-Index-Report_2023.pdf.
[2] Borgonovi, Francesca, Flavio Calvino, Chiara Criscuolo, Lea Samek, Helke Seitz, Julia Nania, Julia Nitschke, and Layla O'Kane. "Emerging Trends in AI Skill Demand across 14 OECD Countries." Paris: OECD, October 17, 2023. https://doi.org/10.1787/7c691b9a-en.
[3] OECD. "OECD Skills Outlook 2023," 2023. https://www.oecd-ilibrary.org/content/publication/27452f29-en.
[4] Larsen, Christa, Jenny Kipper, Alfons Schmid, and Marco Ricceri. "The Relevance of Artificial Intelligence in the Digital and Green Transformation of Regional and Local Labour Markets Across Europe: Perspectives on Employment, Training, Placement, and Social Inclusion." Forschung Und Deren Anwendung Im Bereich Des Regionalen Und Lokalen Arbeitsmarktmonitorings Im Transnationalen Vergleich (Veröffentlichungen Des IWAK). Baden-Baden: Nomos Verlagsgesellschaft mbH & Co. KG, 2022. https://doi.org/10.5771/9783957104113.
[5] Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics*, April 1, 2022. https://doi.org/10.1086/718327.
[6] Goldfarb, Avi, Bledi Taska, and Florenta Teodoridis. "Artificial Intelligence in Health Care? Evidence from Online Job Postings." In *AEA Papers and Proceedings*, 110:400–404, 2020. https://doi.org/10.1257/pandp.20201006.

- The 2020 paper *Artificial Intelligence, Firm Growth, and Product Innovation,*[7] by Babina et al., uses this approach to find that firms that invest in AI experience higher growth in sales, employment, and market valuations.

In addition to these policy and academic publications, this approach has been used in many shorter-form articles and dashboards, including Lightcast's 2023 Global Talent Playbook[8], a heatmap of AI in the UK[9], and articles on Ethical AI[10] and Generative AI[11].

Challenges and gaps

While the approach described above can provide substantial insight into AI measurement, there are some gaps and challenges inherent to these data sources. Online labor market data varies in terms of representativeness by industry and country. Some industries, such as Information Technology, are very likely to post jobs online, whereas others, such as Retail, may rely on "help-wanted" signs or other in-person job ads. While it is likely that many job postings that are developing new AI technologies will be posted online, it is possible that some that are using AI technologies to supplement or complement their work are less likely to be posted online.

Similarly, there is imperfect representativeness in online social profile data. Certain professions, such as doctors or academics, are much less likely to have online professional profiles relative to others, such as CEOs or sales workers. Since a substantial portion of AI technological development is likely to happen by workers who have some academic affiliation, this may constitute a larger gap relative to other datasets.

Additionally, while this measurement approach allows for insight on the results of investment in technology, it does not allow for direct tracking of funding. This means that there is likely to be latent AI change that has not yet become a new skill in the labor market, which will not be

[7] Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson. "Artificial Intelligence, Firm Growth, and Product Innovation." *Journal of Financial Economics* 151 (January 2024): 103745. https://doi.org/10.1016/j.jfineco.2023.103745.
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[9] Lightcast. "AI Skills in the UK." Accessed January 31, 2024. https://aiskills.lightcast.io/.
[10] Bittle, Scott. "Few Employers Ask for 'Ethical AI' Skills in Job Postings." Lightcast. Accessed January 31, 2024. https://lightcast.io/resources/blog/ethical-ai-in-job-postings.
[11] O'Kane, Layla. "4 Ways Generative AI Will Change the Job Market." Lightcast. Accessed January 31, 2024. https://lightcast.io/resources/blog/4-ways-generative-ai-will-change-the-job-market.

captured by this approach. For example, if substantial funding is allocated to the use of generative AI in classroom curricula, this may not be directly captured by job postings data, but will likely eventually be captured as the knowledge of uses for generative AI grows and employers start to request it more frequently. Other inputs that are pivotal to policy conversations are also easy to miss in online labor market data, such as education credentials and especially microcredentials. Employers tend to request skills but are less likely to request specific ways for workers to demonstrate that they have a skill, such as a certificate or a microcredential.

As AI becomes increasingly popular, it is also possible that employers or job-seekers will add AI-related skills to their postings or profiles as a matter of hype, rather than because they truly demand or supply that skill. To hedge against this, researchers have categorized AI skills as being "generic" and "specific" and required at least one "specific" AI skill in a posting or profile to count as an AI job/profile.[12]

In order to track these skills, the data needs a flexible and robust skills taxonomy, which is often provided in various forms by data collection companies. This taxonomy enables tracking of key AI skills and, with regular updates, new and emerging technologies. Without access to a skills taxonomy, a similar approach could be used relying on keyword searching, though this can be prone to false positives and require substantial quality review.

Last but certainly not least, while this data is widely available, it is not publicly available. Online labor market data is largely collected by the private sector, and it is expensive to aggregate, clean, and maintain. It also requires relatively frequent taxonomy updates to keep abreast of current changes and allow for new occupations to be measured and emerge. These updates are best taken on by a dedicated team that works with these data and can understand how best to synthesize and aggregate text data for use by researchers (an AI problem in and of itself!).

[12] Borgonovi, Francesca, Flavio Calvino, Chiara Criscuolo, Lea Samek, Helke Seitz, Julia Nania, Julia Nitschke, and Layla O'Kane. "Emerging Trends in AI Skill Demand across 14 OECD Countries." Paris: OECD, October 17, 2023. https://doi.org/10.1787/7c691b9a-en.

Next steps

The technological challenges associated with maintaining these big data systems are non-negligible, but the good news is that many states and government agencies already have access to these data through third-parties.

In the short-term, greater access to clean postings and profile data could help workforce agencies, state and local governments, and other key stakeholders make decisions more quickly. While a working definition of an AI sector is pre-built into Lightcast's Analyst tool, not all stakeholders have access and this definition may not suit every priority. Funding should be expanded to ensure that these agencies can access data on top in-demand AI skills and jobs so that they can know where best to use other available dollars to shore-up training to support AI.

In the medium-term, measurement of AI impact should extend beyond a purely economic endeavor and should move to include other considerations, such as ethics. Recent research[13] published jointly by my team at Lightcast and the OECD looked at job postings for AI workers in 14 OECD countries. Within those job postings, we looked for mentions of ethical AI, including keywords such as "AI ethics", "responsible AI", "ethical AI", and others across languages used in these countries. A tiny fraction (less than 2%) of AI job postings in all countries studied requested these skills in their AI workers. In the United States, where new generative AI technologies are developing rapidly, this proportion is only 0.5%. Without an understanding of how these tools are being used and in conjunction with what other skills, AI is likely to continue being a source of fear for many who feel their work may be supplanted by technology.

In the long-term, flexibility will be the key to ensuring AI measurement can continue to become more precise and insightful. Updating the skills that are AI-relevant or use AI with frequency, as well as continuously assessing if there are new opportunities to measure AI in different ways, will require more collaboration between data collection sources. Additionally, potentially adding new AI job titles, occupations, or sectors to government-maintained taxonomies would help measure other variables such as employment. This would require additional collaboration between stakeholders, including data aggregators and official government statistical offices, such as the Bureau of Labor Statistics.

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[13] Borgonovi, Francesca, Flavio Calvino, Chiara Criscuolo, Lea Samek, Helke Seitz, Julia Nania, Julia Nitschke, and Layla O'Kane. "Emerging Trends in AI Skill Demand across 14 OECD Countries." Paris: OECD, October 17, 2023. https://doi.org/10.1787/7c691b9a-en.

Informing other emerging technologies

In addition to measuring AI, there are several other critical or emerging technologies to which this "basket-of-skills" approach using online labor market data has already been applied. This section reviews key emerging technologies, digital jobs and green jobs, and provides examples of published works that use this approach to measure the technological impact on the economy.

Digital Jobs:

- *APEC Closing the Digital Skills Gap*[14], which looks at digital job growth in the US, Canada, the UK, Australia, New Zealand, and Singapore.
- *Digitalization in the German Labor Market*[15] by O'Kane et. al, 2020, which analyzes digital skill growth in Germany and finds digitalization is correlated with socioeconomic factors such as education level, gender, and income.
- *No Longer Optional: Employer Demand for Digital Skills*[16] by Nania et. al, 2019 which shows how pervasive digital skills have become across a wide range of jobs in the UK.

Green Jobs:

- Curtis and Marinescu's *Green Energy Jobs in the US: What Are They, and Where Are They*[17] (2022) use a skills approach to define green jobs, and find that both solar and wind jobs have more than tripled since 2010, and that growth of renewable energy leads to the creation of relatively high paying jobs.
- Working Nation's *Green Jobs Now*[18] report shows substantial growth in green jobs and estimates that 51M workers could be reskilled into green jobs in future.

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[14] "APEC Closing the Digital Skills Gap Report: Trends and Insights." APEC Human Resources Development Working Group, December 2020. https://www.apec.org/docs/default-source/publications/2020/12/apec-closing-the-digital-skills-gap-report/220_hrd_apec-closing-the-digital-skills-gap-report_rev.pdf?sfvrsn=5c89561f_1.

[15] O'Kane, Layla, Rohit Narasimhan, Julia Nania, and Bledi Taska. "Digitalization in the German Labor Market: Analyzing Demand for Digital Skills in Job Vacancies." Bertelsmann Stiftung, July 2020. https://www.bertelsmann-stiftung.de/fileadmin/files/user_upload/STUDIE_Burning_Glass_EN_FINAL.pdf.

[16] Nania, Julia, Hal Bonella, Dan Restuccia, and Bledi Taska. "No Longer Optional: Employer Demand for Digital Skills," n.d. https://assets.publishing.service.gov.uk/media/5cfe713fed915d097daca4b5/No_Longer_Optional_Employer_Demand_for_Digital_Skills.pdf.

[17] Curtis, E. Mark, and Ioana Marinescu. "Green Energy Jobs in the US: What Are They, and Where Are They?" Working Paper. Working Paper Series. National Bureau of Economic Research, August 2022. https://doi.org/10.3386/w30332.

[18] Sederberg, Rachel, Will Markow, and Joel Simon. "Green Jobs Now." Working Nation. Accessed January 31, 2024. https://workingnation.com/wp-content/uploads/2023/08/WorkingNation_Lightcast_GreenJobsNow_August2023.pdf.

- Saussay et al. find in *Who's Fit for the Low-Carbon Transition? Emerging Skills and Wage Gaps in Job Ad Data*[19] that low-carbon job ads have higher skill requirements, particularly for technical skills, and the wage premium for low-carbon job ads has declined over time.

These examples demonstrate that online labor market data can help measure new, emerging technologies and provide a wide range of insight into how economies are changing in real time as a result of these technologies. This basket-of-skills approach is flexible, dynamic, and adaptable, lending itself well to as-yet undefined or undiscovered technologies.

Conclusion

While online labor market data has its challenges,it can provide insight that other available data sources cannot. Its two main strengths, frequent (even daily) updates and large sample sizes, are particularly relevant for new technologies which may just be beginning to impact small pockets of the economy. It is also often forward-looking, with employers posting job postings for a future hire, representing a view of the labor market to come rather than the current stock of the labor market. This can help policymakers and other stakeholders forecast effects of new technologies and track rates of adoption and impact in real-time. Alongside other data sets, online labor market data analyzed using a basket-of-skills approach should be a key metric for measuring artificial intelligence and other emerging sectors.

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[19] Saussay, Aurélien, Misato Sato, Francesco Vona, and Layla O'Kane. "Who's Fit for the Low-Carbon Transition? Emerging Skills and Wage Gaps in Job Ad Data." SSRN Scholarly Paper. Rochester, NY, October 27, 2022. https://doi.org/10.2139/ssrn.4260227.

Appendix

A working definition based on AI skills and skill clusters for measuring AI is provided below, based on Lightcast's skills taxonomy.

Artificial Intelligence: AI/ML Inference, AIOps (Artificial Intelligence For IT Operations), Applications Of Artificial Intelligence, Artificial General Intelligence, Artificial Intelligence, Artificial Intelligence Development, Artificial Intelligence Markup Language (AIML), Artificial Intelligence Systems, Azure Cognitive Services, Baidu, Cognitive Automation, Cognitive Computing, Computational Intelligence, Cortana, Ethical AI, Expert Systems, Explainable AI (XAI), IPSoft Amelia, Intelligent Control, Intelligent Systems, Interactive Kiosk, Knowledge Engineering, Knowledge-Based Configuration, Knowledge-Based Systems, Multi-Agent Systems, Open Neural Network Exchange (ONNX), OpenAI Gym, Operationalizing AI, Reasoning Systems, Watson Conversation, Watson Studio, Weka

Autonomous Driving: Advanced Driver Assistance Systems, Autonomous Cruise Control Systems, Autonomous System, Autonomous Vehicles, Guidance Navigation And Control Systems, Light Detection And Ranging (LiDAR), OpenCV, Path Analysis, Path Finding, Remote Sensing, Unmanned Aerial Systems (UAS)

Generative Artificial Intelligence: ChatGPT, Generative Adversarial Networks, Generative Artificial Intelligence, Large Language Modeling, Prompt Engineering, Variational Autoencoders

Natural Language Processing (NLP): AI Copywriting, ANTLR, Amazon Textract, Apache OpenNLP, BERT (NLP Model), Chatbot, Computational Linguistics, Conversational AI, Dialog Systems, Fuzzy Logic, Handwriting Recognition, Hugging Face (NLP Framework), Hugging Face Transformers, Intelligent Agent, Intelligent Virtual Assistant, Kaldi, Language Model, Latent Dirichlet Allocation, Lexalytics, Machine Translation, Microsoft LUIS, Natural Language Generation, Natural Language Processing, Natural Language Programming, Natural Language Toolkits, Natural Language Understanding, Optical Character Recognition (OCR), Screen Reader, Semantic Analysis, Semantic Parsing, Semantic Search, Sentiment Analysis, Seq2Seq, Speech Recognition, Speech Recognition Software, Speech Synthesis, Statistical Language Acquisition, Text Mining, Text-To-Speech, Tokenization, Voice Assistant Technology, Voice Interaction, Voice User Interface, Word Embedding, Word2Vec Models, fastText

Neural Networks: Apache MXNet, Artificial Neural Networks, Autoencoders, Caffe2, Chainer (Deep Learning Framework), Convolutional Neural Networks, Cudnn, Deep Learning, Deep Learning Methods, Deeplearning4j, Evolutionary Acquisition Of Neural Topologies, Fast.ai, Keras (Neural Network Library), Long Short-Term Memory (LSTM), OpenVINO, PaddlePaddle, Recurrent Neural Network (RNN), TensorFlow

Machine Learning: AWS SageMaker, AdaBoost (Adaptive Boosting), Adversarial Machine Learning, Apache MADlib, Apache Mahout, Apache SINGA, Apache Spark, Association Rule Learning, Automated Machine Learning, Autonomic Computing, Azure Machine Learning, Boosting, CHi-Squared Automatic Interaction Detection (CHAID), Classification And Regression Tree (CART), Cluster Analysis, Collaborative Filtering, Confusion Matrix, Cyber-Physical Systems, Dask (Software), Data Classification, Dbscan, Decision Models, Decision Tree Learning, Dimensionality Reduction, Dlib (C++ Library), Ensemble Methods, Feature Engineering, Feature Extraction, Feature Learning, Feature Selection, Gaussian Process, Genetic Algorithm, Google AutoML, Gradient Boosting, H2O.ai, Hidden Markov Model, Hyperparameter Optimization, Inference Engine, K-Means Clustering, Kernel Methods, Kubeflow, Loss Functions, MLOps (Machine Learning Operations), MLflow, Machine Learning, Machine Learning Algorithms, Machine Learning Methods, Machine Learning Model Monitoring And Evaluation, Machine Learning Model Training, Markov Chain, Matrix Factorization, Meta Learning, Microsoft Cognitive Toolkit (CNTK), ModelOps, Naive Bayes Classifier, Perceptron, Predictive Modeling, PyTorch (Machine Learning Library), PyTorch Lightning, Random Forest Algorithm, Recommender Systems, Reinforcement Learning, Scikit-Learn (Python Package), Semi-Supervised Learning, Soft Computing, Sorting Algorithm, Supervised Learning, Support Vector Machine, Test Datasets, Theano (Software), Torch (Machine Learning), Training Datasets, Transfer Learning, Transformer (Machine Learning Model), Unsupervised Learning, Vowpal Wabbit, Xgboost, mlpack (C++ Library)

Robotics: Advanced Robotics, Bot Framework, Cognitive Robotics, Motion Planning, Nvidia Jetson, Robot Framework, Robot Operating Systems, Robotic Automation Software, Robotic Liquid Handling Systems, Robotic Programming, Robotic Systems, SLAM Algorithms (Simultaneous Localization And Mapping), Servomotor

Visual Image Recognition: 3D Reconstruction, Activity Recognition, Computer Vision, Contextual Image Classification, Digital Image Processing, Eye Tracking, Face Detection, Facial Recognition, Gesture Recognition, Image Analysis, Image Matching, Image Recognition, Image Segmentation, Image Sensor, Imagenet, Machine Vision, Motion Analysis, Object Recognition, OmniPage, Pose Estimation

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