The Fearless Future: Global AI Jobs Barometer 2025

AI makes people more valuable

Methodology Appendix

We analysed job ads from data provider Lightcast

Country Name	Number of observations
United States	406,046,340
United Kingdom	114,033,805
Germany	74,453,370
France	50,085,742
Canada	21,708,544
Mexico	18,358,437
Brazil	16,824,532
Italy	15,323,940
Netherlands	15,122,502
Singapore	14,188,461
Belgium	14,031,387
Australia	13,785,544
Poland	13,183,592
Spain	12,389,469
Sweden	10,280,912
Switzerland	7,258,722
Malaysia	5,909,311

Country Name	Number of observations
Denmark	4,598,335
Ireland	3,860,132
South Africa	3,406,455
New Zealand	3,367,391
Hong Kong, SAR	3,029,620
United Arab Emirates	2,095,148
Norway	1,825,464

Total observations

841,389,319

Lightcast's updated data methodology

Changes stem from improved deduplication, sectoral mapping, AI taxonomy, and data standardisation

1

Noise Reduction & Improved Skill Detection

The deduplication model has been enhanced, leading to a reduction in data duplication.

2

More Accurate Deduplication Model

Previously, deduplication used ISCO (436 occupations); now, it relies on Lightcast Occupations (1,900 levels) and Job Titles (>70,000).

3

Standardisation of Non-English-Speaking Countries' Data

The format for non-English-speaking countries' data shifted, improving sectoral allocations through more accurate mapping mechanisms.

4

Refined AI Skills Taxonomy

The AI skills taxonomy has been expanded, leading to a rise in the number of jobs classified as 'AI jobs'. Additionally, AI skill libraries have been fine-tuned, incorporating additional tools and skills. This results in a larger AI taxonomy compared to last year.

We use the IMF's classification for augmentable vs automatable jobs

We introduce the IMF's complementarity variable

AI Exposure Index: The augment and automate analysis includes only the occupations for which the AI exposure is greater than 0.5 on a scale of 0 to 1 (the top half of all observations).

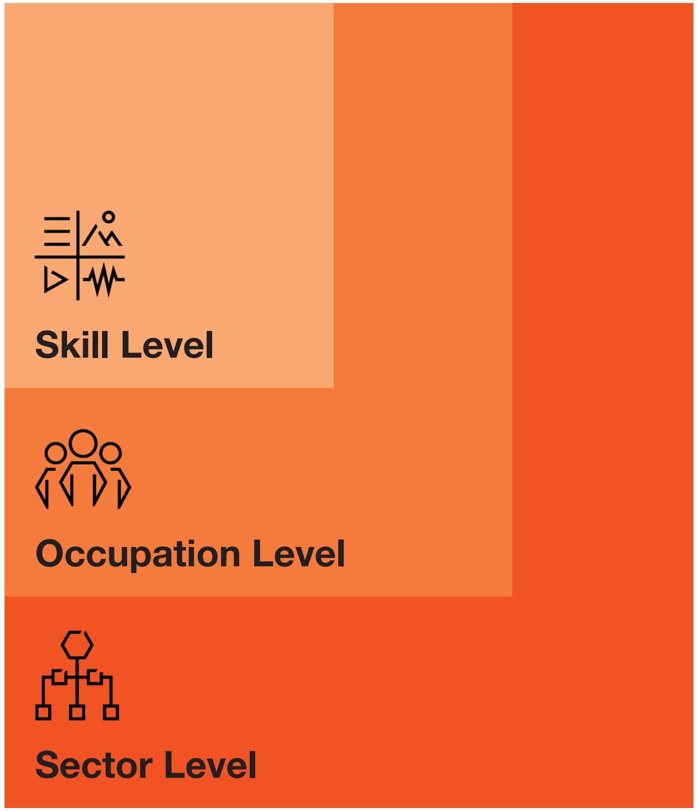
IMF Complementarity Index: Extends Felten's work to assess AI's potential to automate or augment key tasks for occupations.

We re-base the complementarity variable so that all occupations are between 0 and 1.

Augmented jobs: high AI exposure (greater than 0.5) and high complementarity (greater than 0.5) are poised for augmentation with AI enhancing productivity and wages (e.g., surgeons, judges).

Automated jobs: high AI exposure (greater than 0.5) and low complementarity (less than 0.5) are poised for automation as AI replaces tasks, reducing demand (e.g., clerical workers, telemarketers).

Levels of analysis we hope to include



Metrics we include

- Relative growth in Augment and Automate job postings, 2012 to 2024
- Relative growth in Augment and Automate job postings, 2018 to 2024
- Change in job demand for augmented and automated occupations, by country, 2019 to 2024
- Net skill change for augmented and automated occupations, by country, 2019 to 2024

Detailed methodology for key metrics

Metric	Data	Methodology	Levels
Relative growth in AI and all job postings, 2012/18 to 2024, globally	Lightcast: Share of AI jobs and All jobs	We take global Lightcast data for all job postings (global, including all nations listed on the previous slide) and compare the number of all jobs with the number of 'AI jobs'. We take a ratio for the relative number of all and AI jobs compared to 2012/18 levels.	Globally Occupation level
Proportion of total job posts requiring AI related skills, 2012 to 2024	Lightcast: Share of AI jobs	We take economy level Lightcast data for the number of job postings with an 'AI skill(s)' listed. We compare core countries over time to show the relative growth in the number of jobs listed with 'AI skills'.	Globally and by country Occupation level
Proportion of total job postings requiring AI related skills by sector, 2012 to 2024	Lightcast: Share of AI jobs	We take global Lightcast data for the number of job postings with an 'AI skill(s)' listed. We compare across different sectors over time to show the relative growth in the number of jobs listed with 'AI skills'.	Globally Occupation and sector level
Change in demand for all skills in all jobs against exposure to AI, 2019 to 2024	Lightcast: Change in demand for skills	We take global Lightcast data for demand for skills for each year by skill category on a global level. The demand (%) is the number of times a given skill category is mentioned (in a given year) over all skills.	Globally Occupation level
Number of job postings relative to 2012/18 by AI exposure	Lightcast: Change in demand for all jobs	We take Lightcast data on the difference in demand for jobs (grouped by occupation using ISCO codes). We split the demand for jobs into quartiles based on AIOE, with the top quartile being the most exposed to AI. For each quartile we take a ratio of growth from 2012 and compare the quartiles overtime.	Globally Occupation level
Average wage premium for jobs if listed with 'AI skills', 2024	Lightcast: Wage premium for AI jobs compared to all jobs	We take economy level Lightcast data for the difference in wages for a given occupation. We compare, for the same occupation, the difference in wage if the job is or is not listed with 'AI skills'. Thus we estimate the wage premium of 'AI jobs'.	By country Occupation level
The top 5 fastest and top 5 slowest growing skills by category, 2019 to 2024	Lightcast: Demand for skills Felten's AIOE	We take global Lightcast data for demand for skills for each year by skill category on a global level. The demand (%) is the number of times a given skill category is mentioned (in a given year) over all skills.	Globally Skill level

Detailed methodology for key metrics

Metric	Data	Methodology	Levels
Relative growth in Augment and Automate job postings, 2012/18 to 2024	Lightcast: Total postings (with Occ. Code) Felten's AIOE IMF: Complementarity	We take global Lightcast data for all job postings and categorise each posting as either one of Augmented, Automated, or Neither based off their occupation code. We only include occupations for which the AIOE is greater than 0.5 (ie. we include the upper half of observations). We then use the IMF complementarity variable, where the upper half of occupations are considered augmented jobs, and the bottom half are considered automated jobs. We then take a ratio for the relative number of Augment and Automate jobs compared to 2012/18 levels.	Globally Augment and Automate
Change in demand by nation, 2019-2024, all jobs, augmented and automated	Lightcast: Change in demand for all jobs Felten's AIOE IMF: Complementarity	We take Lightcast data on the difference in demand for AI jobs (grouped by occupation using ISCO codes). We use AIOE to compare change in demand relative to AI exposure. We split this data further by augment and automate, using the complementarity variable. We observe the average positive and negative change in demand for skills for augmented and automated jobs.	Globally and by country Occupation level Augment and Automate
Average positive skill change and average negative skill change, for augmented and automated jobs, 2019-2024, globally	Lightcast: Positive and negative change in skills Felten's AIOE IMF: Complementarity	We take global Lightcast data for demand for skills for each year by skill category on a global level. We use both positive and negative change in demand data (2019 to 2024). We split this data further by augment and automate, using the complementarity variable. We observe the average positive and negative change in demand for skills for augmented and automated jobs.	Globally and by country Augment and Automate
The top 5 fastest and top 5 slowest growing skills by category, Augment and Automate Jobs, 2019 to 2024	Lightcast: Demand for skills Felten's AIOE IMF: Complementarity	We take global Lightcast data for demand for skills for each year by skill category on a global level. The demand (%) is the number of times a given skill category is mentioned (in a given year) over all skills. We only include occupations for which the AIOE is greater than 0.5 (ie. we include the upper half of observations). We then use the IMF complementarity variable, where the upper half of occupations are considered augmented jobs, and the bottom half are considered automated jobs.	Globally Skill level Augment and Automate

In analysing the impact of AI Exposure on productivity levels, we adopt a methodology that focuses on three core metrics

Levels of analysis we provide

- Global
- Country level
- Firm level
- Sector level
- Total of all firms/sectors
- By firm size

Metrics we include

For each level of analysis, we assess the following metrics:

- **Change in productivity** between 2018-2023 – turnover per employee (TPE) is calculated by dividing operational revenue by headcount
- **Change in headcount** between 2018-2023 – given as EMPL in the ORBIS dataset
- **Change in wage per employee** between 2018-2023 – wage per employee is calculated by dividing total staff costs by headcount

All three metrics are examined against **AI Industry Exposure** values sourced from Felten (2021). This ultimately allows us to assess the impact of AI exposure on productivity, headcount, and wages at both firm and sector level.

High level methodology

- We start by cleaning the raw Orbis dataset by removing outliers and checking for data completeness.
- We map AI Industry Exposure values sourced from Felten to the NAICS2017 sector codes tagged to the ORBIS data.
- We calculate turnover per employee (TPE) by dividing operational revenue by headcount.
- We calculate wage per employee by dividing total staff costs by headcount.
- We calculate the delta/percentage change for each of the three metrics using the 2018 and 2023 values as our inputs.
- We perform firm level analysis to determine correlation, regression and top quartile to bottom quartile ratios.
- We aggregate our results by 4-digit NAICS sector.
- We calculate weighted percentage changes for TPE, number of employees per company (EMPL) and WAGE using the 2018 and 2023 values as our inputs.
- We perform sector level analysis to determine correlation, regression and top quartile to bottom quartile ratios.
- We split firms into two groupings (‘Large’ and ‘Super Large’) taking an operating revenue in 2023 of $1bn as the threshold.
- We perform the same firm and sector level analysis on the two different groupings of firms.
- We export our data tables into Excel to produce the final charts.

Our productivity analysis includes a range of metrics and our methodology for each metric is outlined below

Metric	Data	Methodology	Level
AI exposure vs growth rate in productivity by sector	Felten: AIIE Orbis: Growth rate in TPE	TPE is calculated by dividing operational revenue by headcount. At sector level we calculate a weighted TPE by dividing the sum of operational revenue across all firms in a sector by the sum of employment across all firms in a sector. The percentage change across the 2018 and 2023 values is then taken as the growth rate.	Globally and by country By sector By firm
AI exposure vs growth rate in headcount by sector	Felten: AIIE Orbis: Growth rate in headcount	Headcount is directly provided in the Orbis data as 'EMPL'. At sector level we calculate a weighted headcount by taking the sum of employment across all firms in a sector. The percentage change across the 2018 and 2023 values is then taken as the growth rate.	Globally and by country By sector By firm
AI exposure vs growth rate in wage per employee by sector	Felten: AIIE Orbis: growth rate in wage per employee	Wage per employee is calculated by dividing total staff costs by headcount. At sector level we calculate a weighted wage per employee by dividing the sum of staff costs across all firms in a sector by the sum of employment across all firms in a sector. The percentage change across the 2018 and 2023 values is then taken as the growth rate.	Globally and by country By sector By firm
AI exposure vs growth rate in productivity by sector, by Large and Super Large firm size	Felten: AIIE Orbis: Growth rate in TPE	Follows methodology from (1) but firms with revenue greater than \$1bn are considered 'Super Large' while firms with revenue between \$50mn and \$1bn are considered 'Large'. The analysis is essentially run twice; once for 'Super Large' firms and once for 'Large' firms.	Globally and by country By sector By firm size By firm
AI exposure vs growth rate in headcount by sector, by Large and Super Large firm size	Felten: AIIE Orbis: Growth rate in headcount	Follows methodology from (2) but firms with revenue greater than \$1bn are considered 'Super Large' while firms with revenue between \$50mn and \$1bn are considered 'Large'. The analysis is essentially run twice; once for 'Super Large' firms and once for 'Large' firms.	Globally and by country By sector By firm size By firm
AI exposure vs growth rate in wage per employee by sector, by Large and Super Large firm size	Felten: AIIE Orbis: Growth rate in wage per employee	Follows methodology from (3) but firms with revenue greater than \$1bn are considered 'Super Large' while firms with revenue between \$50mn and \$1bn are considered 'Large'. The analysis is essentially run twice; once for 'Super Large' firms and once for 'Large' firms.	Globally and by country By sector By firm size By firm

In arriving at our final datasets, we apply a series of assumptions and filters that directly impact the overall firm count

Filter	Rationale	Number of firms affected	Number of surviving firms
Orbis Raw Data (pre-filtered for firms with $50mn+ OPRE)	This is the starting dataset	N/A	280,955
Removal of fewer than 4-digit NAICS/empty cells/missing values for either EMPL19/23 or OPRE19/23	We clean the Orbis dataset and remove any entries that are empty/NA as well as NAICS codes that are not 4 digits	221,740	59,215
Removal of firms from the Orbis dataset that have a 4-digit NAICS code with no direct match in the Felten AIIE paper	We are unable to tag these firms to a corresponding sector-specific AI exposure value	19,492	39,723
Removal of firms that do not have 10 or more employees in 2018 and 2023	We deem 10 employees to be a reasonable threshold for a firm to be considered ‘normal’	1,210	38,513
Removal of firms that have 0 operational revenue in either 2018 or 2023	Operational revenue of 0 is unrealistic in the context of our analysis and we treat these entries as anomalies in the data	25	38,488
Removal of firms that are identified as outliers by the Rosner Outlier Test (where k = 100)	Rosner’s Test is used to detect ‘k’ outliers in a dataset by iteratively removing the most extreme values. In our analysis we set the maximum number of outliers as 100, determined through an eye test of the distribution of the TPE growth data	100	38,388 (TPE/Headcount Table)
Removal of firms that have STAFF costs of 0/NA in either 2018 or 2023	Staff costs of 0 are unrealistic and would cause a calculation error when computing ‘wage per employee’	8770	29,618
Removal of firms that have a ‘wage per employee’ value that falls outside of $1000 - $10,000,000	We filter out the possibility of negative wages and leave the upper bound relatively open, considering filter 4 is already in place	142	29,476 (Wage Table)

Other Filters (Sector Level and Size Level Analysis)

- For sector-based analysis we require a minimum of 5 firms to be included. For size-based sector analysis we reduce this requirement to 3 firms to maintain a sufficient sample size.
- For sector-based analysis we exclude any datapoints where the calculated growth in ‘wage per employee’ across 2018-2023 (‘Wage_Delta’) exceeds 100%. We consider these sectors to be ‘abnormal’ and treat them as outliers relative to the rest of the dataset.

Notes: We apply the wage filters (6 and 7) last, as applying the wage filter before the productivity a nd headcount analysis results in a substantially smaller dataset for the productivity and headcount analysis. As such, we duplicate a parallel dataset to that used in the productivity and headcount analysis and apply the wage filter there. We use this parallel dataset for our wage analysis.

Our analysis considers workforce breakdowns, by national economy and gender

We leverage data from Felten, IMF, and ILOSTAT to produce analysis that breaks down country-specific workforces into quartile AI exposures, assess automation and augmentation potential and analyse gender-specific trends.

Felten's AI Occupational Exposure Index (AIOE): Evaluates the potential for AI to perform key job function, producing an AI exposure score by occupation.

IMF Complementarity Index: Extends Felten's work to assess AI's potential to automate or augment key tasks for occupations.

ILOSTAT Workforce Data: Comprehensive data which breaks down country-specific workforces by occupation and gender.

List of 376 AI Skills used to identify 'jobs that require AI skills'

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)
Intelligent Control
Intelligent Systems
Interactive Kiosk
IPSoft Amelia
Knowledge Engineering
Knowledge-Based Configuration
Knowledge-Based Systems
Multi-Agent Systems
Open Neural Network Exchange (ONNX)
OpenAI Gym
Operationalizing AI
Reasoning Systems
Soft Computing
Swarm Intelligence
Watson Conversation
Watson Studio
Weka
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)
AdaBoost (Adaptive Boosting)
Adversarial Machine Learning
Apache MADlib
Apache Mahout
Apache SINGA
Apache Spark
Association Rule Learning
Attention Mechanisms
Automated Machine Learning
Autonomic Computing
AWS SageMaker
Azure Machine Learning
Boltzmann Machine
Boosting
Bot Framework
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)
Embedded Intelligence
Ensemble Methods
Evolutionary Programming
Expectation Maximization Algorithm
Fast.ai
Feature Engineering
Feature Extraction
Feature Learning
Feature Selection
Game Ai
Gaussian Process
Genetic Algorithm
Google AutoML
Google Cloud ML Engine
Gradient Boosting
H2O.ai
Hidden Markov Model
Hyperparameter Optimization
Inference Engine
K-Means Clustering
Kernel Methods
Kubeflow
LIBSVM
Loss Functions
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)
MLflow
MLOps (Machine Learning Operations)
mlpack (C++ Library)
ModelOps
Naive Bayes Classifier
Objective Function
Oracle Autonomous Database
Perceptron
Predictionio
Programmatic Media Buying
Pydata
PyTorch (Machine Learning Library)
Random Forest Algorithm
Recommender Systems
Reinforcement Learning
Scikit-Learn (Python Package)
Semi-Supervised Learning
Sorting Algorithm
Supervised Learning
Support Vector Machine
Test Datasets
Torch (Machine Learning)
Training Datasets
Transfer Learning
Unsupervised Learning
Variational Autoencoders

Vowpal Wabbit
Xgboost
Amazon Alexa
Amazon Textract
ANTLR
Apache OpenNLP
BERT (NLP Model)
Chatbot
Computational Linguistics
DeepSpeech
Dialog Systems
fastText
Fuzzy Logic
Handwriting Recognition
Hugging Face (NLP Framework)
Intelligent Agent
Intelligent Virtual Assistant
Kaldi
Language Model
Latent Dirichlet Allocation
Lexalytics
Machine Translation
Microsoft LUIS
Natural Language Generation
Natural Language Processing (NLP)
Natural Language Programming
Natural Language Toolkits
Natural Language Understanding
Natural Language User Interface
Nearest Neighbour Algorithm
Nuance Mix
Optical Character Recognition (OCR)
Prompt Engineering
Screen Reader
Semantic Analysis
Semantic Interpretation For Speech Recognition
Semantic Parsing
Semantic Search
Sentiment Analysis
Seq2Seq
Shogun
Speech Recognition
Speech Recognition Software
Speech Synthesis
Statistical Language Acquisition
Text Mining
Text-To-Speech
Theano (Software)
Tokenization
Voice Assistant Technology
Voice Interaction
Voice User Interface
Word Embedding
Word2Vec Models
Apache MXNet
Artificial Neural Networks
Autoencoders
Caffe (Framework)
Caffe2
Chainer (Deep Learning Framework)
Convolutional Neural Networks
Cudnn
Deep Learning
Deep Learning Methods
Deeplearning4j
Evolutionary Acquisition Of Neural Topologies
Generative Artificial Intelligence
ChatGPT
AI Skill (201-250)
Hugging Face Transformers
Large Language Modelling
Transformer (Machine Learning Model)
Generative Adversarial Networks
Keras (Neural Network Library)
Long Short-Term Memory (LSTM)
OpenVINO
PaddlePaddle
Pybrain
PyTorch Lightning
Recurrent Neural Network (RNN)
TensorFlow
Advanced Robotics
Cognitive Robotics
Motion Planning
Nvidia Jetson
Robot Framework
Robot Operating Systems
Robotic Automation Software
Robotic Liquid Handling Systems
Robotic Programming
Robotic Systems
Servomotor
SLAM Algorithms (Simultaneous Localization And Mapping)
3D Reconstruction
Activity Recognition
Computer Vision
Contextual Image Classification
Deck.gl
Digital Image Processing
Eye Tracking
Face Detection
Facial Recognition
General-Purpose Computing On Graphics Processing Units
Gesture Recognition
Image Analysis
Image Matching
Image Recognition
Image Segmentation
Image Sensor
Imagenet
Machine Vision
Mnist
Motion Analysis
Object Recognition
OmniPage
Pose Estimation
Realsense
AI Copywriting
Conversational AI
Predictive Modeling
Synthetic Data Generation
OpenAI Gym Environments
Text Retrieval Systems
Object Tracking
Adobe Sensei
Embedded AI
Deep Reinforcement Learning (DRL)
Vespa
CrewAI
Neuro-Symbolic AI
Incremental Learning
t-SNE (t-distributed Stochastic Neighbor Embedding)
Language Models
Neural Ordinary Differential Equations
Image Super-Resolution
Sequence-to-Sequence Models (Seq2Seq)
Recurrent Neural Networks (RNNs)
Bagging Techniques
Data Version Control (DVC)
Convolutional Neural Networks (CNN)
Topological Data Analysis (TDA)
Residual Networks (ResNet)
Reinforcement Learning from Human Feedback (RLHF)
Variational Autoencoders (VAEs)
Scene Understanding
Meta-Reinforcement Learning
Reinforcement Learning (RL)
Concept Drift Detection
Text to Speech (TTS)
Thermal Imaging Analysis
Image Captioning
Meta-Learning
Image Inpainting
Digital Twin Technology
Semantic Kernel
Text Summarization
Natural Language Understanding (NLU)
Natural Language Generation (NLG)
Retrieval Augmented Generation
Dynamic Routing
Multimodal Learning
Qdrant
Sentence Transformers
Weaviate

Data Sovereignty
Microsoft Copilot
Automated Data Cleaning
Neural Architecture Compression
Langgraph
Instance Segmentation
Distributed Machine Learning
Summarization Methods
Bayesian Belief Networks
Small Language Model
AutoGen
Neural Architecture Search (NAS)
Graph Neural Networks (GNNs)
PineCone
Spiking Neural Networks
Multimodal Models
Gradient Boosting Machines (GBM)
AI Personalization
Knowledge Representation
Edge Intelligence
Knowledge Distillation
Support Vector Machines (SVM)
Federated Learning
AI Security
Artificial Intelligence Risk
Agentic Systems
AI Testing
Generative AI Agents
DALL-E Image Generator
Google Bard
Stable Diffusion
Amazon Comprehend
Amazon Lex
Amazon Polly
Dialogflow (Google Service)
Disambiguation
GPT-3 (NLP Model)
Information Extraction
Language Identification
Lemmatization
N Gram
Named Entity Recognition
NLTK (NLP Analysis)
Part-of-Speech Tagging
Question Answering
Relationship Extraction
Sirikit
Speech Enhancement
Speech Processing
Speech Technology
Sphinx Speech Recognition
Text Classification
Voice Technology
Word-Sense Disambiguation
K-Nearest Neighbors Algorithm
Artificial Consciousness
LightGBM
Intelligent Automation
Nuance Nina Virtual Assistant
Azure OpenAI
Azure AI Studio
AWS Bedrock
Google Assistant
Automated Planning And Scheduling
LangChain
GitHub Copilot
Human AI Interaction
Few Shot Learning
AI Research
AI Innovation
AI Agents
Agentic AI
Zero Shot Learning
AI Safety
AI Alignment
Graph Algorithms
Time Series
Text Processing
PySpark
Databricks
Neural Machine Translation (NMT)

How we calculate net skill change

The net skill change is a measure of the change in the frequency of skills required by employers for a particular occupation. This metric and its associated methodology to be calculated was developed by Harvard economists, David Deming and Kadeem Noray (2020).

Below we present the formula and walk through an example.

In short, the net skill change takes the absolute value of each skill change for an occupation and sums them. As it measures the absolute value the value is always positive. It is capturing skill changes be they positive or negative and adding them. The more changes in skills demanded by an employer be they demanded more or less (positive or negative), the higher this net skill change value.

Example:

If skill A is mentioned 50 times in 2019 and then 65 times in 2023 (and we assume job postings remained constant in both time periods at 100 for example). The skill change would be 65/100 - 50/100 = 15/100 = **+0.15.**

If skill B is mentioned 30 times in 2019 and then 25 in 2023 (in 100 postings in both periods), the skill change would be 25/100 - 30/100 = -5/100 = **-0.05.**

The net skill change the sum of the absolute values:

Net skill change for job X = 0.15 + 0.05 = **0.20.**

Formula:

$$Net\ Skill\ Change_{o,t2,t1} = \sum_{s=1}^{S} Abs\left[\left(\frac{Skills^{s}_{o,t2}}{JobAds_{o,t2}}\right) - \left(\frac{Skills^{s}_{o,t1}}{JobAds_{0,t1}}\right)\right]$$

2025 Global AI Jobs Barometer

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