Simulating Automation Timelines Through Labor-Capability Modeling

A probabilistic forecasting pipeline assessing the future impact of AI on labor markets in India and Nigeria.

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Abstract: A Policy-Aware "Forecast of Work"

This system addresses critical uncertainty regarding the pace and focus of AI-driven job automation by fusing three core data streams:

Occupational Skill Data

Detailed skill requirements (e.g., O*NET) to establish technical automation thresholds.

AI Benchmark Scores

Quantitative time-series data projecting future AI capability growth.

Real-Time Policy Signals

Sourced via GDELT for India and Nigeria, acting as dynamic multipliers or constraints.

The expected output is a live, policy-aware "Forecast of Work" dashboard for strategic workforce planning.

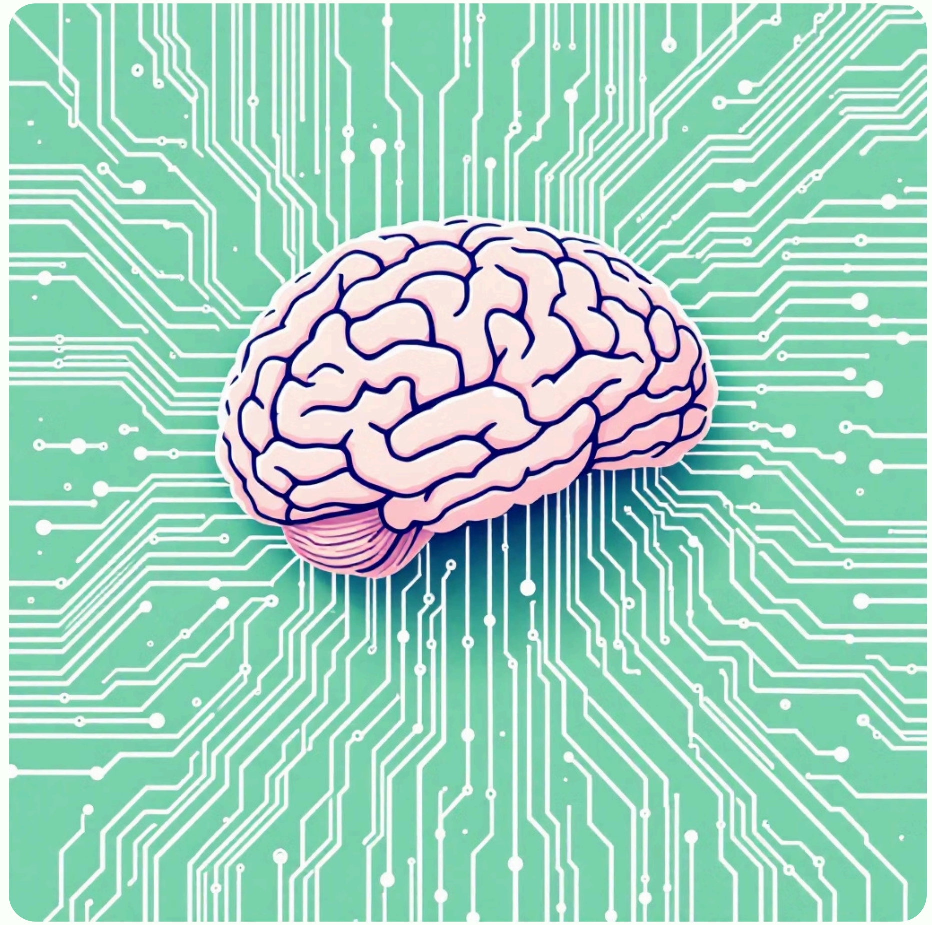
Introduction: Bridging the Knowledge Gap

The non-linear advancement of AI creates significant uncertainty. Our core objective is to simulate the interaction between accelerating AI capability growth and human labor skill requirements.

The Critical Questions

- Which economic tasks will be automated first?
- How soon will this fundamentally reshape entire industries?

The system uses granular occupational data (O*NET) and quantitative AI performance benchmarks (MMLU-Pro, SWE-Bench) to generate a dynamic forecast with uncertainty intervals.



Core Data Sources for Modeling

The forecasting pipeline relies on a diverse set of high-quality, quantitative data streams.

O*NET 30.0

894 standardized occupations with detailed skill, knowledge, and ability ratings (importance and level).

AI Capability Benchmarks

Five key benchmarks: MATH, SWE-bench, MedQA, MMLU-Pro, and GPQA for measuring AI performance.

Policy & Capacity Indicators

World Bank data (WDI, WGI) on R&D, electricity access, GDP, and government effectiveness.

Real-Time Policy Signals

GDELT data capturing AI-related regulatory actions, investment shifts, and workforce initiatives.

Methodology: Skill-to-Capability Mapping

We systematically link human labor skills to dynamic AI capability growth to establish the 2024 AI performance baseline for 35 O*NET skills.

1

Data Sourcing & Baseline

Utilized O*NET and top Benchmark Scores from five frontier AI task domains (LLM stats).

2

Semantic Mapping

Calculated Cosine Similarity between skill and benchmark descriptions to identify the two most relevant benchmarks.

3

Collated Score

Job skill's 2024 capability score derived from the mean of the two corresponding benchmark scores.

This provides the essential quantitative link to assess a job's current automation vulnerability.

Forecasting Automation Timelines (2035)

We project capability growth using Monte Carlo simulation (2,000 iterations) and integrate policy factors for a nuanced forecast.

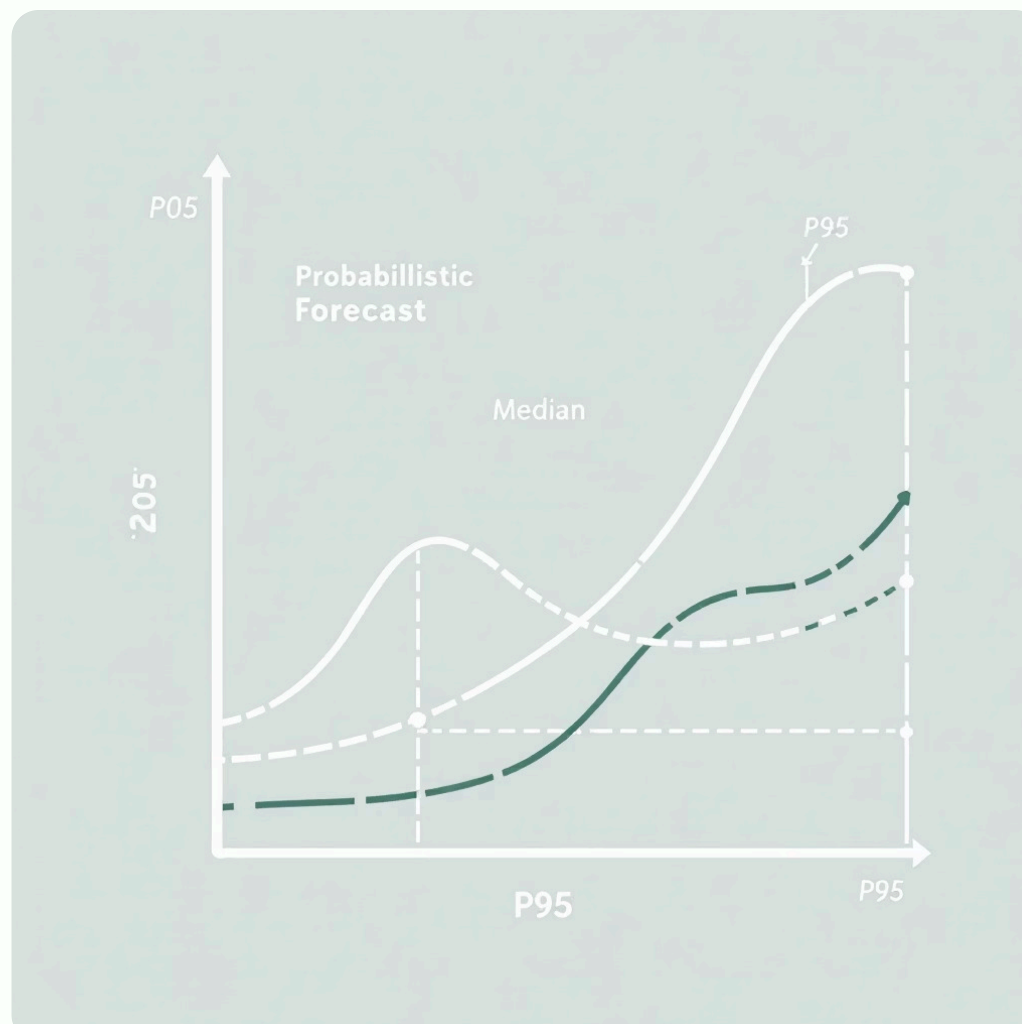
Simulation & Aggregation

- **Growth Rates:** Historical AI performance gains modeled as annual growth (9% to 33%).
- **Monte Carlo:** 2,000 iterations simulate innovation unpredictability (20% standard deviation).
- **Job-Level Data:** Aggregated with a demand decay factor (0.5% annual rate) and vulnerability defined by the skill with the highest AI capability.

Policy-Aware Adjustments

A country-specific capacity score (India/Nigeria) shifts the effective year of automation vulnerability.

Policy events (e.g., investment, regulation) act as dynamic multipliers or constraints, amplifying or attenuating vulnerability forecasts.



Results: Polarization of Automation Risk

The forecast reveals a significant polarization, with high-skill cognitive roles facing the greatest vulnerability.

Most Vulnerable (Vulnerability Score > 0.89)

Highly skilled, knowledge-intensive roles:

- Mathematicians (0.946)
- Judges (0.938)
- Mental Health Counselors (0.929)

Least Vulnerable (Vulnerability Score < 0.42)

Roles defined by physicality and unstructured environments:

- Slaughterers and Meat Packers (0.374)
- Dishwashers (0.395)
- Agricultural Sorters (0.399)

The average occupation faces only a 3.9% vulnerability increase through 2035.

Acceleration in Technical and Skilled Trades

A specific set of occupations shows extreme acceleration in risk, suggesting an immediate need for workforce planning.

20.1%

Service Technicians

Highest projected increase in automation risk.

14.0%

Computer Programmers

High acceleration as AI guides complex coding and repair processes.

This trend highlights the challenge of reskilling technicians and programmers to collaborate with sophisticated AI tools.

Discussion: Model Limitations and Future Directions

The current model provides a strong foundation but has limitations that future research must address.

Embodied AI Gap

The model lacks benchmarks for embodied AI (robotics, tactile manipulation), leading to an underestimation of automation resistance in physical jobs (e.g., Slaughterers).

Linear Extrapolation

Reliance on linear extrapolation of AI progress may fail to capture breakthrough or plateau dynamics in capability growth.

Lagging Skill Mappings

O*NET mappings may lag behind the emergence of new, hybrid human-AI collaborative roles, requiring dynamic skill tracking.

Conclusion: Evidence-Based Workforce Planning

This study provides the first comprehensive, benchmark-grounded projection of occupational vulnerability to AI through 2035.

Strategic Insight

Enables evidence-based planning that transcends speculative automation discourse.

Probabilistic Framework

Provides confidence bounds (P05 to P95) for robust scenario planning under uncertainty.

Maintain Accuracy

Regular recalibration of benchmark-to-occupation mappings is essential as AI capabilities evolve.