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Artificial Intelligence as a Labor Market Shock: Cross-Country Evidence on Unemployment

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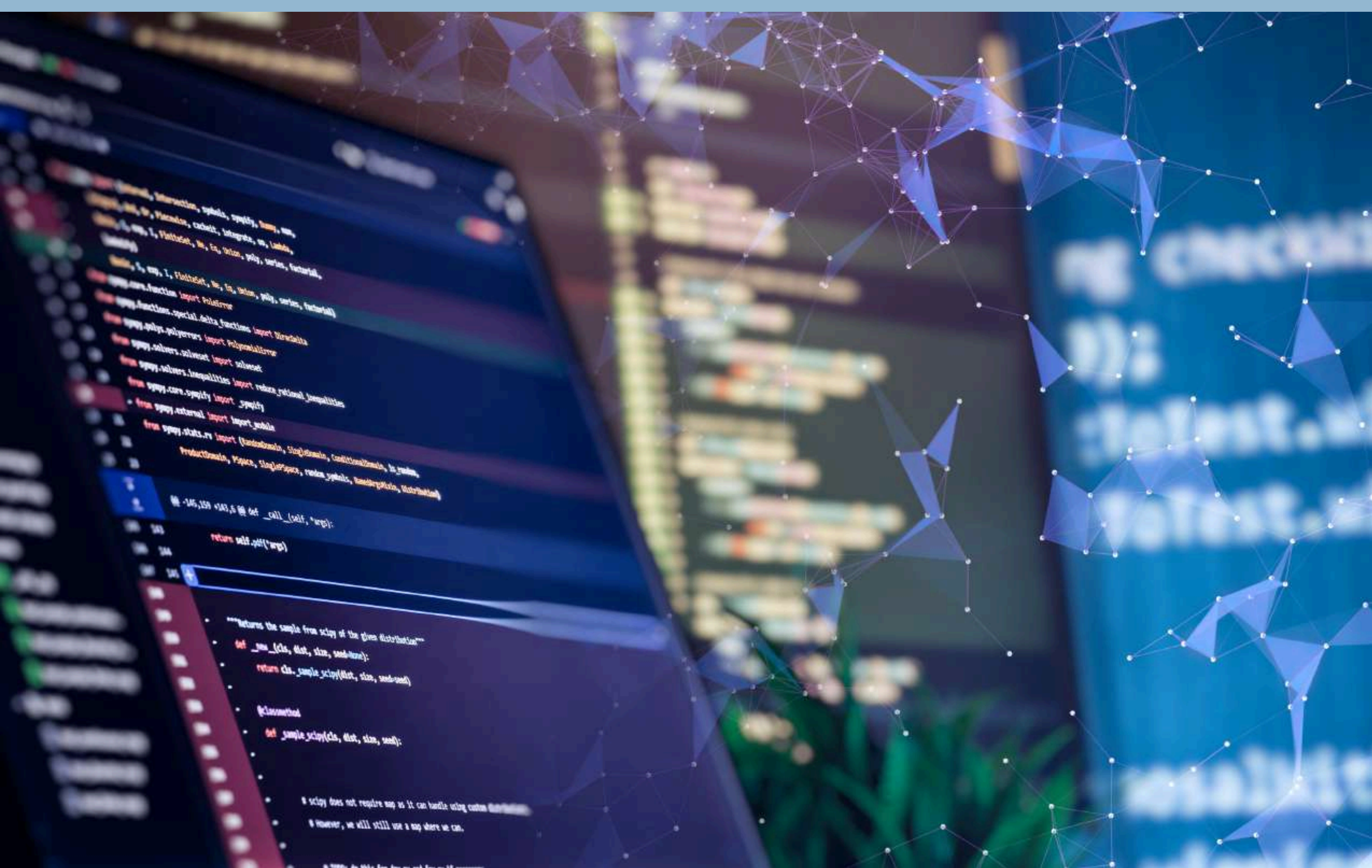

Artificial Intelligence as a Labor Market Shock: Cross-Country Evidence on Unemployment

Introduction

Artificial intelligence (AI) has been emerging as a major technological force with the potential to transform labor markets across various industries and occupations. As AI's ability to perform routine tasks increases, concerns regarding how technological innovation may affect labor demand and employment across different economies have grown. Past empirical research on large exogenous economic shocks provides useful frameworks for studying their macroeconomic effects. For example, Autor, Dorn, and Hanson (2013) show that U.S. regions more exposed to Chinese imports experienced larger job losses and labor market disruptions. Their findings demonstrate how differences in economic structure can cause global shocks to have heterogeneous labor-market effects.

Our empirical study applies a similar framework to the global expansion of artificial intelligence since 2018, and especially to the expansion of large language models after 2022. These developments represent major technological shifts influencing labor demand across occupations and sectors. This leads to our research question: How does exposure to artificial intelligence affect unemployment across countries, and do countries with higher AI exposure experience differential labor-market outcomes following the diffusion of AI technologies after 2018 and the expansion of large language models after 2022?

To answer this question, we adopt an interaction framework inspired by Rajan and Zingales (1998) and use cross-country differences in occupational composition to measure structural exposure to AI. If AI affects labor demand, countries whose employment structures are more concentrated in AI-exposed occupations should experience greater unemployment changes.

Literature Review

Our proposal draws on two key empirical foundations in applied macroeconomics: the trade-exposure literature, particularly The China Syndrome: Local Labor Market Effects of Im port Competition in the United States by Autor et al. (2013), and the cross-industry interaction methodology developed by Rajan and Zingales in Financial Dependence and Growth (1998).

The key contribution of the China-shock literature is the shift-share methodology, which defines exposure by interacting industry employment shares with national import-penetration measures. Our replication builds on the same logic, but replaces trade exposure with exposure to AI. More specifically, it replaces import penetration with industry-specific AI intensity, and regional employment shares with country-specific employment shares fixed at 2010.

In addition, AI-exposure intensity is based on Felten, Raj, and Seamans (2019), who con struct an AI Occupational Exposure Index by linking advances in AI capabilities to the tasks performed in different occupations. We combine these exposure scores with country-specific employment shares to construct a country-level AI exposure index using pre-AI employment structures in order to reduce reverse-causality concerns.

We also extend the Rajan and Zingales approach by introducing an additional country-level variable: AI institutional preparedness, measured using the IMF AI Preparedness Index (2024). This allows us to examine not only whether AI exposure matters, but also whether readiness to absorb technological change moderates its labor-market effects.

Data

We aim to construct a cross-country panel dataset covering 75 countries over the period 2010–2024.[1] Labor-market outcomes will be taken from the International Labour Organization (ILO). Using unemployment-rate records from the ILO provides a consistent measure of labor market conditions across countries. We will also obtain macroeconomic control variables from the World Bank's World Development Indicators (WDI) database. These include GDP per capita, GDP growth, the share of services in GDP, the industrial sector's share of GDP, and inflation (CPI). These controls account for macroeconomic structure, economic growth, and price stability, all of which may independently affect labor-market outcomes.

Our study will further incorporate the Artificial Intelligence Preparedness Index from the International Monetary Fund (IMF) to capture a country's readiness to adapt to technological change. This index reflects digital infrastructure, human capital, innovation capacity, and regulatory readiness, allowing us to distinguish countries that are relatively more prepared to integrate AI technologies from those with weaker institutional and technological foundations.

[1] Refer to Appendix B in the draft for steps taken to arrive at the sample size.

Finally, we construct an AI-exposure measure using occupational task data from the O*NET Resource Center and occupation-level AI-exposure scores developed by Felten, Raj, and Sea mans. These occupation-level measures are then aggregated to the country level using employment composition records from the ILO.

Methodology

Our dependent variable is the unemployment rate based on ILO modeled estimates, providing cross-country unemployment data. We also control for various macroeconomic variables that may independently influence unemployment, such as GDP per capita, services value added as a share of GDP, industry value added as a share of GDP, population, inflation rate, and GDP growth.

We use the natural logarithm of GDP per capita to capture proportional cross-country differences in income. AI-exposure weights correspond to occupational employment shares in 2010, which serves as the base year for the pre-AI period. Since the resulting index reflects structural labor-market characteristics, we treat it as time-invariant. We additionally examine whether institutional readiness affects the impact of AI exposure by merging the dataset with the IMF Artificial Intelligence Preparedness Index (AIPI), which reflects a country's readiness to adopt and benefit from AI technologies.

The key variables in our model are as follows. The dependent variable, U_{ct}, is the unemployment rate in country *c* and year *t*. The key independent variable, Exposurec, measures country-level AI exposure. $Post_t$ is an indicator equal to one for years 2018–2024, reflecting the period during which AI adoption and machine-learning deployment began to scale globally. $Covid_t$ is an indicator equal to one for the years 2020–2021 in order to account for the pandemic shock.

Our empirical framework uses a difference-in-differences model with country and year fixed effects:

$$U_{ct} = \alpha + \beta_1(Exposure_c \times Post_t) + \beta_2(Exposure_c \times Covid_t)$$
$$+ \beta_3(Exposure_c \times Post_t \times AIPI_c) + \gamma X_{ct} + \mu_c + \lambda_t + \varepsilon_{ct}$$

where X_{ct} represents macroeconomic control variables, μ_c denotes country fixed effects, and λ_t denotes year fixed effects. Standard errors will be clustered at the country level to account for within-country correlation and heteroskedasticity.

The coefficients of interest are interpreted as follows. β_1 measures whether countries with higher AI exposure experienced differential unemployment changes after the spread of AI tech nologies. A positive value would suggest higher unemployment in more exposed countries, whereas a negative value would suggest productivity gains or labor reallocation effects. β_2 captures whether countries with greater AI exposure experienced different unemployment out comes during the COVID-19 period. β_3 indicates whether AI preparedness moderates the un employment effects of AI exposure. A negative coefficient would imply that countries with stronger AI readiness are better able to absorb technological shocks.

Policy Proposal

In our replication study, the technological shock differs fundamentally from the China import shock. AI exposure causes technological substitution and augmentation of tasks within existing occupations, rather than completely displacing occupations in the initial phases. AI technologies can automate routine cognitive tasks such as data processing and programming assistance, thereby gradually reshaping the task composition of occupations rather than eliminating entire job categories immediately. As a result, unemployment may begin through task reallocation before more visible labor displacement occurs.

Based on our preliminary research, policy responses should focus on facilitating worker adjustment to the evolving nature of tasks within occupations. Our first recommendation is that governments should prioritize AI-oriented reskilling systems to help workers transition toward tasks that complement automation. AI diffusion shifts labor demand toward higher order digital and analytical skills while reducing demand for repetitive cognitive tasks that can be automated. For instance, Singapore has implemented programs such as SkillsFuture and the AI Apprenticeship Programme, which provide professional training in data science, machine learning, and AI-related skills. In India, initiatives such as the IndiaAI Mission and Skill India have begun incorporating AI-literacy modules to prepare the workforce for technology-driven occupational shifts.

In addition, policymakers should strengthen labor-market transition mechanisms that sup port worker mobility across occupations and sectors. AI effects are often first reflected through reduced hiring rather than immediate job destruction (Figure 1 in Appendix 5). Accordingly, policies such as wage subsidies, unemployment insurance, job-matching platforms, and retrain ing support can help workers transition toward emerging technology-intensive jobs. Germany's Federal Employment Agency, for example, provides digital retraining and job-matching pro grams to prepare workers for automation- and AI-driven changes.

Furthermore, countries should continue increasing investment in AI preparedness and dig ital infrastructure to ensure that AI adoption leads to productivity gains rather than large-scale labor displacement. The current coverage of AI is much lower than the theoretical coverage in various fields, according to the recent report by Anthropic (Figure 2 in Appendix 5). Initiatives that involve expanding broadband connectivity, strengthening data governance infrastructure, and financially supporting AI adoption among small-and-medium-size enterprises (SMEs) can help firms to simultaneously integrate AI technologies and maintain employment stability. The European Union's Digital Europe Programme is one example of such an approach.

Conclusion

In conclusion, our replication study aims to show how exposure to artificial intelligence influences cross-country labor-market outcomes by analyzing changes in unemployment patterns after the diffusion of AI technologies. AI shocks differ from trade shocks like the China import shock because AI primarily affects employment by changing the nature of tasks within existing occupations rather than by causing immediate job redundancies.

Our research replicates established empirical frameworks to provide evidence on whether economies more exposed to AI technologies experience differential unemployment outcomes after major technological change. The study contributes to the growing literature on technological change by examining the effects of AI on labor-market adjustment and hiring patterns. Understanding these patterns is important for designing policies that support worker transitions while enabling economies to benefit from technological innovation. More broadly, the study aims to inform policy responses to AI-led labor-market shifts.

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Appendix 1: Variable Construction

Table 1: Variable Construction

Variable	Source	Construction
Unemployment rate (uem_ilo)	ILOSTAT / World Bank WDI	Annual unemployment rate (% of labor force)
AI Exposure	Felten et al. (AI Oc cupational Exposure In dex) and O*NET	Country-level exposure constructed using occupation-task mapping
GDP per capita	World Bank WDI	Logged to control for development differ ences
Services share	World Bank WDI	Percentage of GDP from services sector
Industry share	World Bank WDI	Industry value added as percentage of GDP
Inflation	World Bank WDI	CPI inflation (annual percentage)
GDP growth	World Bank WDI	Annual real GDP growth rate
AI Preparedness Index	IMF AIPI	Used to split countries into high vs low preparedness groups

AI Exposure Construction:

The country-level AI exposure index is constructed using occupation-level AI exposure scores and each country's occupational employment structure. Following the exposure-based empirical design used in the trade-shock literature, we aggregate occupational exposure to the country level using pre-determined employment shares.

The AI exposure index for country c is defined as:

$$\text{Exposure}_c = \sum_{0} s_{co,2010} \cdot \text{AI}\mathit{Exp}_o$$

where:

- Exposure_c represents the overall AI exposure of country c.
- $s_{co,2010}$ is the share of occupation o in total employment in country c in 2010.
- AIExp_o denotes the AI exposure score for occupation o, based on the occupation-level exposure measures developed by Felten, Raj, and Seamans.

Using employment shares fixed in 2010 ensures that the exposure measure reflects preexisting labor market structure rather than adjustments that occurred after the diffusion of artificial intelligence technologies.

Appendix 2: Country Sample Selection

This section presents comparative analysis of Own Source Revenue (OSR) performance across various municipal corporations

Table 2: Country Sample Selection

Step	Countrie s
Initial WDI panel	266
AI exposure data available	87
After matching ISO codes	75

Table 3: Final Sample of Countries

Albania	Argentina	Armenia
Australia	Austria	Bangladesh
Belgium	Bosnia and Herzegov ina	Bulgaria
Cambodia	Canada	Chile
Colombia	Costa Rica	Croatia
Cyprus	Czechia	Denmark
Dominican Republic	Ecuador	El Salvador
Estonia	Finland	France
Georgia	Germany	Ghana
Greece	Guatemala	Honduras
Hungary	Iceland	India
Indonesia	Ireland	Italy

Jamaica	Japan	Laos
Latvia	Liberia	Lithuania
Luxembourg	Malta	Mauritius
Mexico	Mongolia	Namibia
Netherlands	North Macedonia	Norway
Pakistan	Papua New Guinea	Paraguay
Peru	Poland	Portugal
Romania	Russian Federation	Serbia
Slovenia	South Africa	Spain
Sri Lanka	Sweden	Switzerland
Thailand	Timor-Leste	Togo
Tunisia	Turkiye	Uganda
Uruguay	Vanuatu	Vietnam

Note: The table above contains the countries included in the final estimation sample after merging the AI exposure dataset, macroeconomic indicators, unemployment data, and the AI Preparedness Index. The final panel dataset includes 75 countries observed between 2010 and 2024.

Appendix 3: Final Regression Model

Our regression models the relationship between artificial intelligence exposure and unemployment using a panel fixed-effects specification.

$$U_{ct} = \alpha + \beta_1(Exposure_c \times Post_t) + \beta_2(Exposure_c \times Covid_t) + \beta_3(Exposure_c \times Post_t \times AIPI_c) + \gamma X_{ct} + \mu_c + \lambda_t + \varepsilon_{ct}$$

Where:

- U_{ct} represents the unemployment rate in country c at time t.
- $Exposure_c$ denotes the country-level AI exposure index constructed using occupational exposure measures aggregated based on each country's employment composition.
- $Post_t$ is an indicator variable equal to 1 for years after the global diffusion of modern AI technologies (post-2018) and 0 otherwise.
- $Covid_t$ is an indicator variable equal to 1 for the pandemic years 2020–2021 and 0 otherwise.
- $AIPI_c$ represents the Artificial Intelligence Preparedness Index, which measures a country's institutional readiness to adopt and benefit from AI technologies.
- X_{ct} represents macroeconomic control variables including GDP per capita, GDP growth, sectoral composition, inflation, and population.
- μ_c represents country fixed effects that control for time-invariant characteristics of countries.
- λ_t represents year fixed effects that capture global shocks affecting all countries in a given year.
- ε_{ct} represents the error term.

Appendix 4: Summary Statistics and Regression Results

Table 4: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Unemployment rate (%)	1125	7.656	5.805	0.119	34.007
AI Exposure Index	1125	-0.226	0.307	-1.041	0.170
Log GDP per capita	1125	9.250	1.276	6.199	11.833
Log Population	1125	16.221	1.638	12.381	21.095
Services share of GDP (%)	1116	58.242	9.126	30.449	81.815
Industry value added	1116	1.27×10^{11}	2.37×10^{11}	5.80×10^{7}	1.67×10^{12}
Inflation (CPI)	1116	4.758	9.724	-2.097	219.884
GDP growth	1125	2.978	3.943	-20.522	31.726

Table 5: AI Exposure and Unemployment: Fixed Effects Regression Results

Variables	Full Sample	High AIPI Countries	Low AIPI Countries
Exposure × Post-2018	-1.871**	0.109	-0.763
	(0.699)	(2.139)	(1.457)
Exposure × COVID	1.249**	-0.378	1.501**
	(0.480)	(1.117)	(0.720)
Exposure × LLM-2022	1.373**	-5.867**	1.854
	(0.668)	(2.341)	(1.191)
Log GDP per capita	-3.479***	-8.023***	-1.449
	(1.165)	(1.125)	(1.259)
Log Population	23.821***	19.492***	28.754***
	(4.655)	(4.504)	(8.202)
Services share of GDP	0.108**	0.260***	0.080*
	(0.052)	(0.084)	(0.039)
Industry value added in GDP	8.46×10^{-13}	4.31×10^{-12}	3.34×10^{-12}
	(2.08×10^{-12})	(2.14×10^{-12})	(4.72×10^{-12})
Inflation (CPI)	-0.020*	-0.069*	-0.012
	(0.011)	(0.035)	(0.007)
GDP Growth	-0.077**	-0.135**	-0.043
	(0.034)	(0.059)	(0.034)
Constant	-352.569***	-238.614***	-459.162***
	(76.975)	(77.757)	(136.234)

Table 6: Model Statistics

Statistic	Full Sample	High AIPI Countries	Low AIPI Countries
Observations	1,108	551	544
Countries	75	37	37
Country Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Clustering	Country	Country	Country
R^2	0.915	0.858	0.944
Within R^2	0.359	0.386	0.390
Root MSE	1.778	1.652	1.803

Standard errors are clustered at the country level to account for heteroskedasticity and serial correlation within countries over time. Because AI exposure is time-invariant at the country level, its main effect is perfectly collinear with country fixed effects and is therefore omitted from the regression. Similarly, the time indicators for the post-AI diffusion period (Post 2018), the COVID-19 shock, and the expansion of large language models after 2022 are absorbed by year fixed effects. Consequently, identification comes from the interaction terms between AI exposure and the post-period indicators, which capture how unemployment patterns evolve differently in countries depending on their structural exposure to AI following the diffusion of AI technologies and major global shocks.

Appendix 5: Supporting Graphs

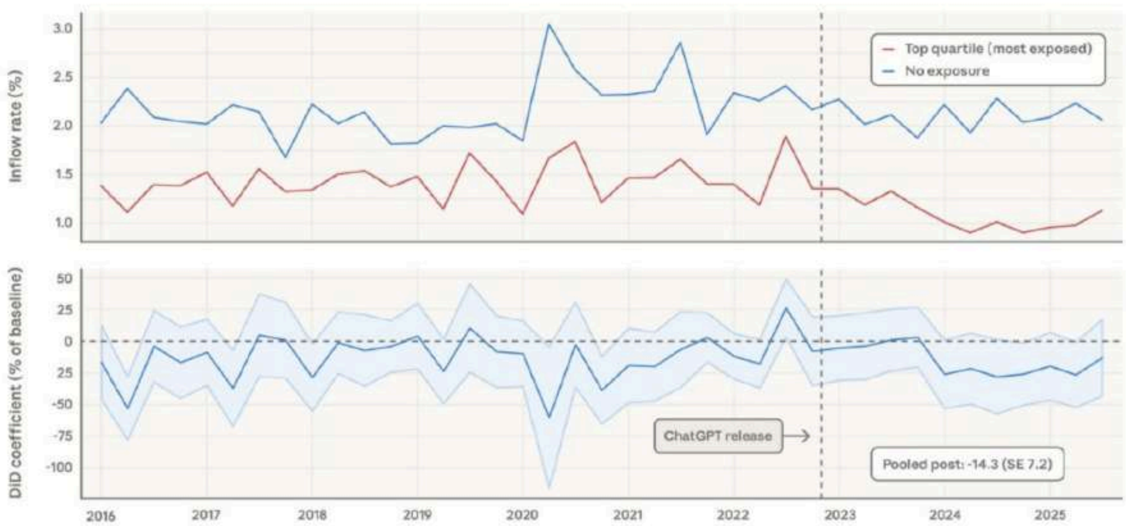

Figure 1: AI Exposure and New Job Starts for Young Workers aged 22–25

Source: Nowcasting the Impact of AI on the Labor Market, Anthropic (2026).

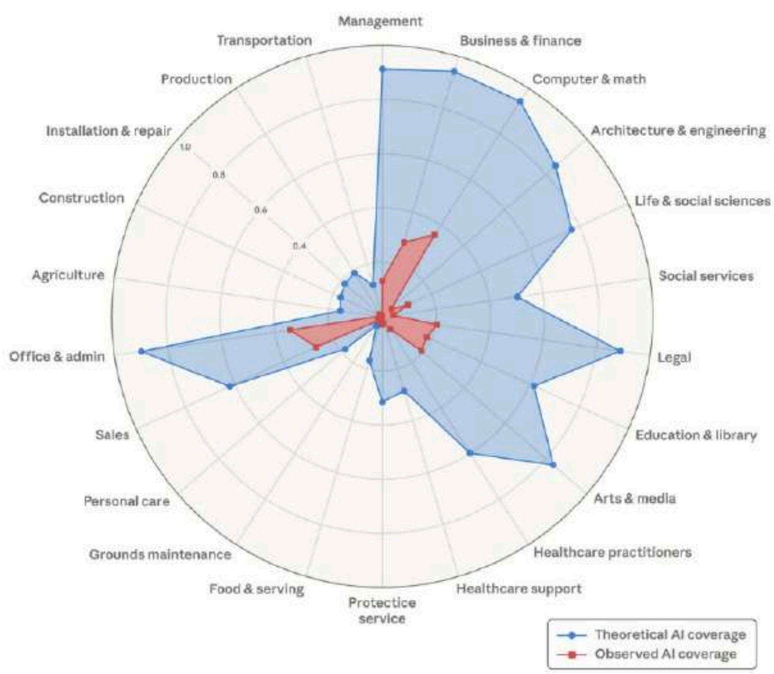

Figure 2: Theoretical vs Observed AI Coverage in Different Occupations

Source: Nowcasting the Impact of AI on the Labor Market, Anthropic (2026).

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