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Labour Market Impacts of Artificial Intelligence: A Critical Review of a New Measurement Framework and Early Empirical Evidence

Commentary on: Massenkoff, M. & McCrory, P. (2026). *Labor market impacts of AI: A new measure and early evidence*. Anthropic Research Report, March 5, 2026.

Abstract: *Massenkoff and McCrory (2026) introduce a novel metric — Observed Exposure — designed to quantify the extent to which artificial intelligence is actively automating occupational tasks, as distinct from what AI is theoretically capable of performing. Drawing on the O*NET occupational database, task-level exposure estimates from Eloundou et al. (2023) and usage data from Anthropic's proprietary Economic Index, the authors construct occupation-level AI exposure scores and evaluate their association with unemployment trends and hiring patterns in the United States. The study finds no statistically significant increase in unemployment for highly exposed workers since late 2022, though it reports suggestive evidence of reduced hiring among workers aged 22–25 in exposed occupations. This note reviews the study's methodological contributions, discusses notable limitations — including the inherent conflict of interest in a developer-authored study — and situates the findings within the broader empirical literature.*

Keywords: *Artificial Intelligence, Labour Markets, Occupational Exposure, Task Automation, Unemployment, LLMs*

1. Overview and Motivation

The question of how AI affects employment has attracted substantial research attention, yet establishing reliable causal estimates has proved methodologically difficult. Massenkoff and McCrory (2026) note that prior technology-displacement forecasts — including estimates of job offshorability and industrial-robot penetration — have produced mixed or contested results, underscoring the need for prospective frameworks rather than post-hoc attribution. The authors' stated aim is to establish a replicable baseline before large-scale effects emerge, so that future analyses can plausibly separate AI-driven displacement from concurrent macroeconomic forces such as business cycle fluctuations and trade policy changes.

The central conceptual contribution is a distinction between theoretical LLM capability and observed deployment. Prior exposure indices (e.g., Eloundou et al., 2023) characterise what models could do; Massenkoff and McCrory seek to measure what models are doing in professional, automated settings. This gap is the study's analytical centrepiece and a genuine addition to the methodological toolkit.

2. Methodology

The Observed Exposure measure is constructed from three inputs. The O*NET database supplies enumerated task lists for approximately 800 US occupations. Theoretical feasibility ratings (β) from Eloundou et al. (2023) score each task as 1 (performable by an LLM alone), 0.5 (requiring supplementary tools) or 0 (infeasible). Observed usage data — drawn from Anthropic's Economic Index covering August and November 2025 — determine whether a theoretically feasible task has seen sufficient work-related deployment in practice. A task is treated as "covered" only if it is both theoretically capable and observably deployed in professional contexts. Fully automated implementations receive full weight; augmentative (human-assisted) usage is weighted at 0.5. Task scores are aggregated to the occupation level weighted by time-on-task, then matched to Current Population Survey (CPS) respondents for labour market outcome analysis.

3. Key Findings

The study reports four principal findings:

Capability–deployment gap: Observed AI coverage is markedly lower than theoretical capability. In Computer & Math occupations, for example, 94% of tasks are rated theoretically feasible, yet observed coverage stands at 33%, indicating substantial unused automation potential across the occupational spectrum.

Most exposed occupations: Computer programmers (74.5%), customer service representatives (70.1%), data entry keyers (67.1%) and medical records specialists (66.7%) rank among the most exposed. Approximately 30% of workers register zero measured exposure, including cooks, mechanics and personal care workers.

Employment growth correlation: BLS projections for 2024–2034 show a modest negative association with observed exposure: each 10 percentage point increase in coverage corresponds to a 0.6 percentage point reduction in projected growth. This correlation is absent when using theoretical exposure alone, which the authors cite as partial validation of the Observed Exposure measure.

Unemployment and hiring outcomes: A difference-in-differences analysis finds no statistically significant increase in unemployment for the most exposed workers relative to the unexposed since late 2022 (pooled coefficient: +0.0020, SE 0.0019). However, a marginally significant 14% decline in job-finding rates for workers aged 22–25 entering exposed occupations is documented in the post-ChatGPT period (SE 7.2). No equivalent decline is observed for workers over 25.

4. Critical Assessment

The Observed Exposure metric constitutes a meaningful methodological improvement over purely theoretical indices. Weighting automated over augmentative use is conceptually coherent with the displacement hypothesis and the explicit prospective design — establishing a baseline prior to widespread effects — is sound scientific practice.

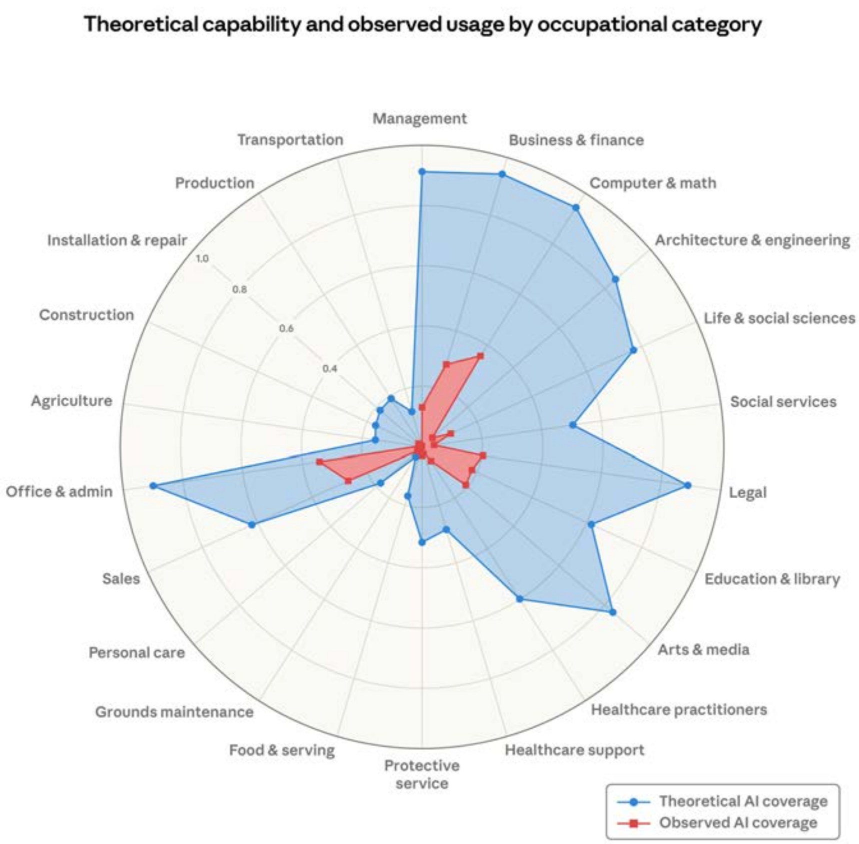
Nonetheless, several limitations require acknowledgement. Most significantly, the usage data derive exclusively from Anthropic's Claude platform. This creates a structural conflict of interest: the organisation producing the AI being studied is also the source of the deployment data used to assess its impact. Independent replication using administrative records, competing platform data or enterprise survey data is necessary before the findings can be treated as externally valid. The authors make the data publicly available, which is commendable, but does not resolve the underlying concern.

Second, the Eloundou et al. (2023) capability ratings reflect model capacities as of early 2023. Given the pace of LLM development since that date, the theoretical ceiling has likely risen, potentially causing the β measure to understate current feasibility. The authors note this limitation and indicate the metric will be updated. Third, the young-worker hiring finding, while consistent with Brynjolfsson et al. (2025), carries a wide standard error and is subject to competing interpretations: young workers who did not enter exposed occupations may have remained in existing jobs, enrolled in further education or exited the labour force — none of which would register as unemployment in CPS data.

5. Conclusion

Massenkoff and McCrory (2026) offer a technically careful and timely addition to the empirical literature on AI and employment. The Observed Exposure framework provides a more deployment-grounded basis for tracking displacement risk than prior capability indices and the absence of detectable aggregate unemployment effects as of early 2026 is a substantively important null result. It does not, however, foreclose future disruption as AI deployment scales and model capabilities advance.

The conflict of interest arising from developer-authored research using proprietary platform data remains the study's central credibility constraint. Readers should weigh the findings accordingly, while recognising the value of the framework itself. Independent replication and future iterations incorporating broader usage data, updated capability assessments and outcomes data for recent graduates in exposed fields will be essential to establishing firmer conclusions.



Theoretical capability and observed exposure by occupational category

Share of job tasks that LLMs could theoretically perform (blue area) and our own job coverage measure derived from usage data (red area).

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