Discussion of “Beyond Exposure: Predicting AI Adoption Based on Comparative Advantage”

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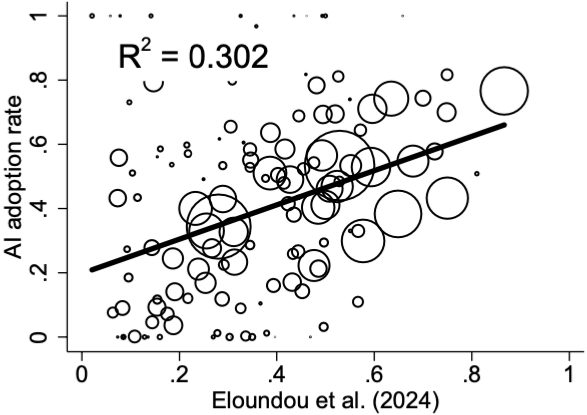
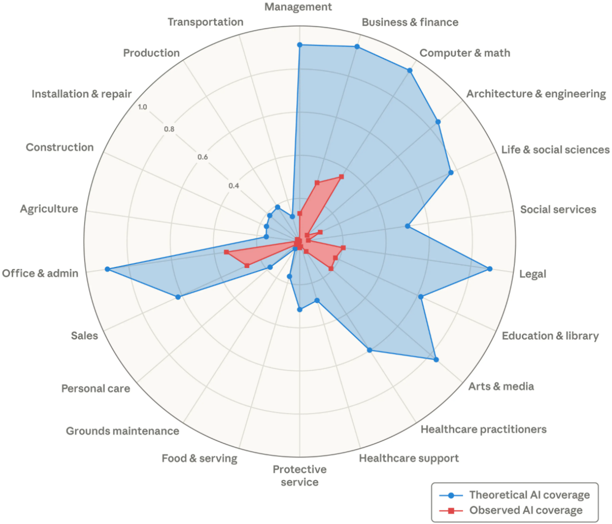
Motivation for the paper



Similar findings in recent Anthropic data



This Paper

- Key observation: AI adoption depends not just on technology, but also on costs. Workers will adopt if:

$$\frac{Z_k^{AI}}{r_k} > \frac{Z_{ik}^{\text{worker}}}{w_{io}}$$

  - Exposure measures capture only Z_k^{AI}
  - The question is not "Can AI do this?" but "Is AI worth using?"

- Key findings:
  - Accounting for worker comparative advantage + user costs substantially improves the ability to explain observed adoption
  - The largest quantitative role comes from inferred task-level user costs

Outline for Discussion

$$\frac{Z_k^{AI}}{r_k} > \frac{Z_{ik}^{\text{worker}}}{w_{io}}$$

1. Measurement of Z_{ik}^{worker}

2. Measurement of Z_k^{AI}

How does the paper recover worker comparative advantage?

1. Step 1: Estimate occupation-specific returns to demographics

$$\log w_{io} = \sum_j X_{ij}\beta_{oj} + FE_o + \epsilon_{io}$$

2. Step 2: Use task shares to “invert” wage returns into task productivity

$$\beta_{oj} = \sum_k \alpha_{ok}\beta_{kj}$$

3. Step 3: Recover worker productivity by task

$$Z_{ik}^{\text{worker}} = \sum_j X_{ij}\beta_{kj}$$

4. Step 4: Infer user costs from remaining adoption gaps

What could go wrong?

1. Wages may reflect institutions, not productivity
   - Public-sector pay, monopsony (Jäger–Naidu–Schoefer 2022)
   - e.g. Teachers may earn institutional wage premia unrelated to task productivity
   - $\Rightarrow \log(\hat{Z}^{\text{worker}}/\hat{w})$ biased *down* in teacher-intensive tasks
   - $\Rightarrow$ AI advantage looks artificially strong $\Rightarrow \widehat{r}_k$ biased *down*
2. Within-occupation task sorting
   - Educated clerks draft/summarize; less educated do filing
   - Same α_{ok} for both $\Rightarrow$ mismatch flows into user costs

$\Rightarrow$ Do these issues matter empirically?

(i) Re-estimate on workers in establishments *without* sectoral bargaining coverage

(ii) Re-estimate β_k using only homogenous occupations (identification doesn't need all 129 occupations)

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1. Measurement of Z_{ik}^{worker}
2. **Measurement of** Z_k^{AI}

Exposure measures and current AI use may be measuring different margins

- Exposure measures are designed to capture theoretical automation potential of the task
  - Question in Eloundou et al: "Can AI reduce completion time by $\geq$ 50%?"
- Actual workplace use in 2024 dominated by "text generation" (e.g. drafting emails, summarizing, editing, coding assistance)

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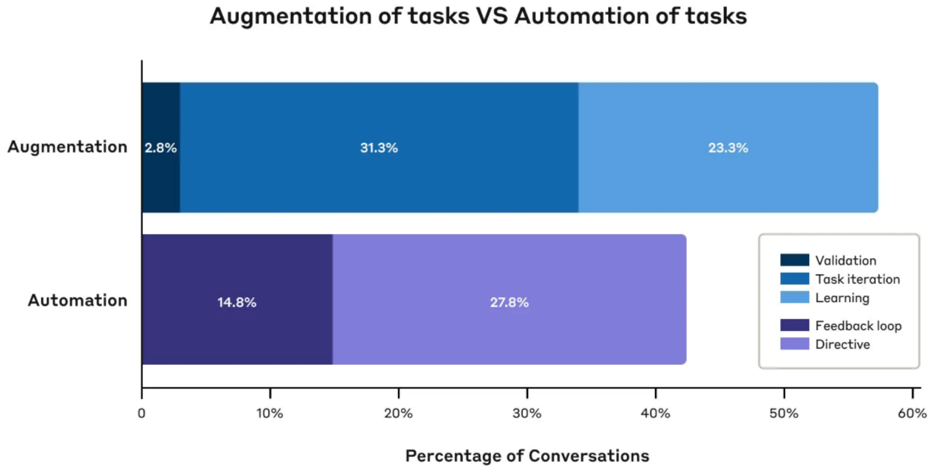
Table 1: AI Adoption by Task

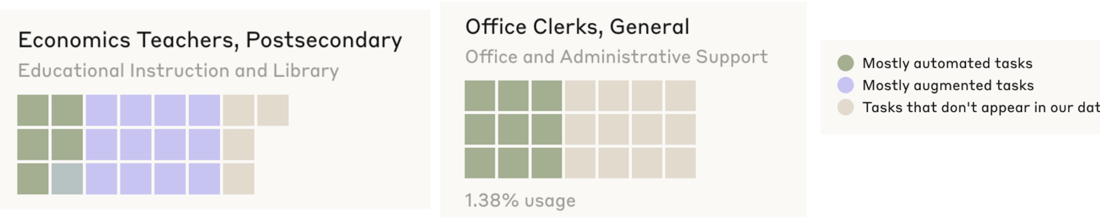
Task	AI adoption share (%)
Text	33.42
Spoken language	15.06
Images/videos	11.83
Diagnoses/analyses	12.63
Cooperative work	5.04
Other	6.83

$\Rightarrow$ Current workplace AI use may primarily involve task augmentation

Anthropic data: Majority of usage is augmenting tasks, not automating



Teachers vs. Office Clerks through the augmentation lens



$\Rightarrow$ Augmentation-heavy occupations look like "low r_k", but maybe Z_k^{AI} is mismeasured because it doesn't include augmentation

Conclusion

- Very nice paper!
  - Comparative advantage clearly matters enormously for understanding AI diffusion
- Clever identification strategy $\Rightarrow$ interpretation of inferred user costs seems like an interesting next step
  - Part of the wedge between exposure and adoption may reflect not only comparative advantage, but also the difference between automation-oriented and augmentation-oriented AI use.