Helping People Choose Careers in the Age of AI

Jennifer L. Steele (steele@american.edu)
Isabella Cruz (ig0189a@american.edu)
American University

Association of Education Finance and Policy

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Outline

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Current impact of AI on jobs is uncertain

- Anthropic: 36% of jobs are using AI for at least a quarter of their tasks (Handa et al., 2025)
- Since 2023, freelance job postings in writing and programming dropped 21% (Demirci et al., 2025)
- Since 2023, employment is falling fastest (up to 13%) for early-career workers in careers with highest exposure to *automation*, not *augmentation* (Brynjolfsson et al., 2025)
- *Automation tasks*, comprising 56% of work ChatGPT queries, 40% of Claude queries, and 70% of Claude API queries, are defined as **directive tasks and feedback loops**
- *Augmentation tasks* involve **iteration, validation, learning, or other queries** (Appel et al., 2025; Handa et al., 2025)

What will jobs look like in the age of AI?

1. Following Autor et al. (2003) and others, we treat 923 occupations (O*NET SOC Codes) as baskets of about 19,265 tasks, 2,069 Detailed Work Activities (DWAs), and 41 Generalized Work Activities (GWAs)

2. For GWAs-level aggregates, we weight automation exposure scores by the relative importance of GWA to the job

3. Examine how ours and 5 other sets of estimates differ by estimation method, job education level, salary, complexity, interest category, and job sector

Outline

We compare six automation-prediction models

Table 1: Models Under Consideration

Article	How	Measure
Steele & Cruz (2026)	Anthropic & GPT queries	% of job tasks automatable
Eloundou et al. (2024)	GPT & human raters	% of job tasks automatable
Felten et al. (2021)	Crowd-sourced	Job ability automation suitability
Webb (2020)	Text-mining for semantic overlap	AI patent filings & job descriptions
Brynjolfsson & Mitchell (2017)	Crowd-sourced w/ rubric	Task suitability for machine learning (SML)
Frey & Osborne (2017)	Human raters	Abilities that are not social, creative, or dexterous

Our empirical measure employs 2025 Claude and OpenAI usage

Using query data from 2025 for Appel et al. (2025) and Chatterji et al. (2025), we define the following:

GWA Exposure
=**80** if in the top decile of Claude, Claude API, or OpenAI queries (>7% of queries)
=45 if 50th to 90th percentiles (1-7% of queries)
=10 if below 50th percentile (<1% of queries)

We aggregate GWAs to jobs, weighting by relative importance

# Pre-Standardized Scales Vary by Model

Table 2: Models Under Consideration

| Model	nJobs	Mean	SD	Min	Max
Steele (2026)	872	39	2.7	31	48
Eloundou (2024)	872	32	19	0	84
Felten (2021)	759	.042	1	-2.7	1.5
Webb (2020)	720	.42	.29	0	1.5
Brynjolf(2018)	923	3.5	.11	2.8	3.9
Frey (2017)	689	.5	.38	.0028	.99

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Tasks vary widely in LLM use patterns

LLM Use by Generalized Work Activity (GWA)

8/4-11/2025 (Claude) or 5/2024-7/2025 (ChatGPT)
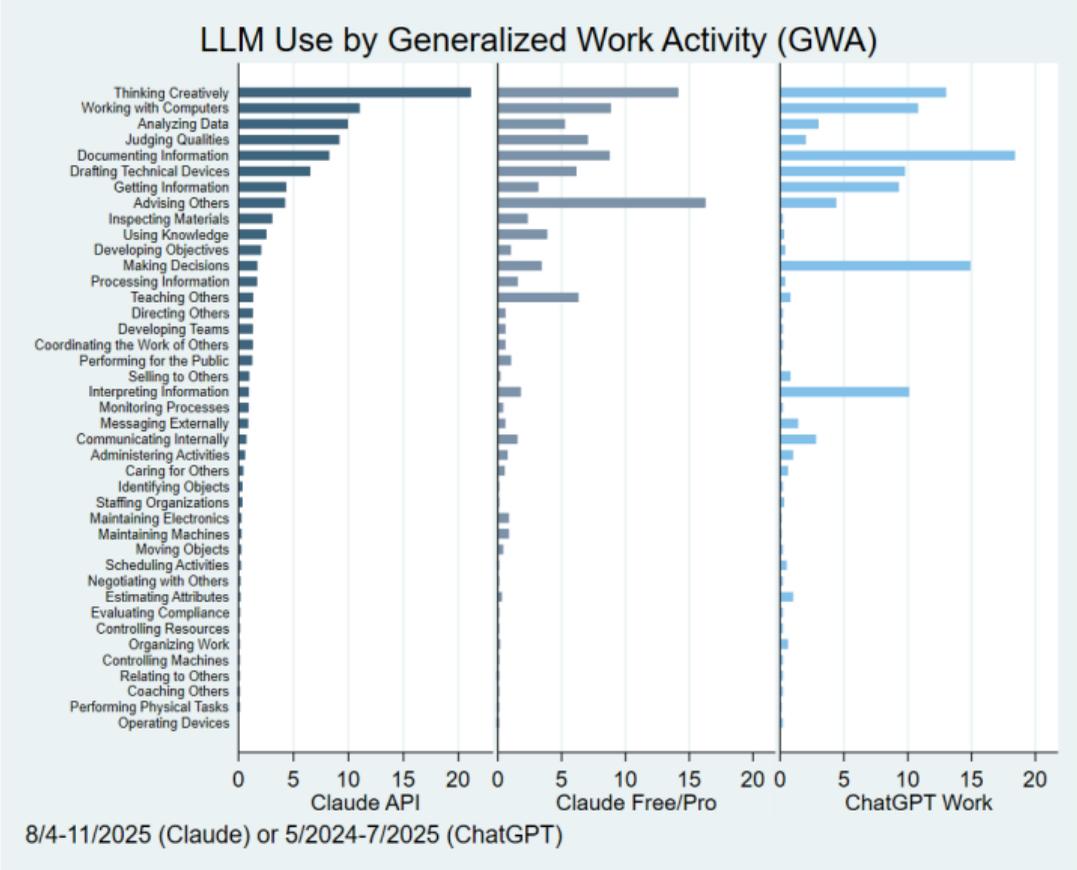
Augmentation is relatively high in coaching, teaching, advising
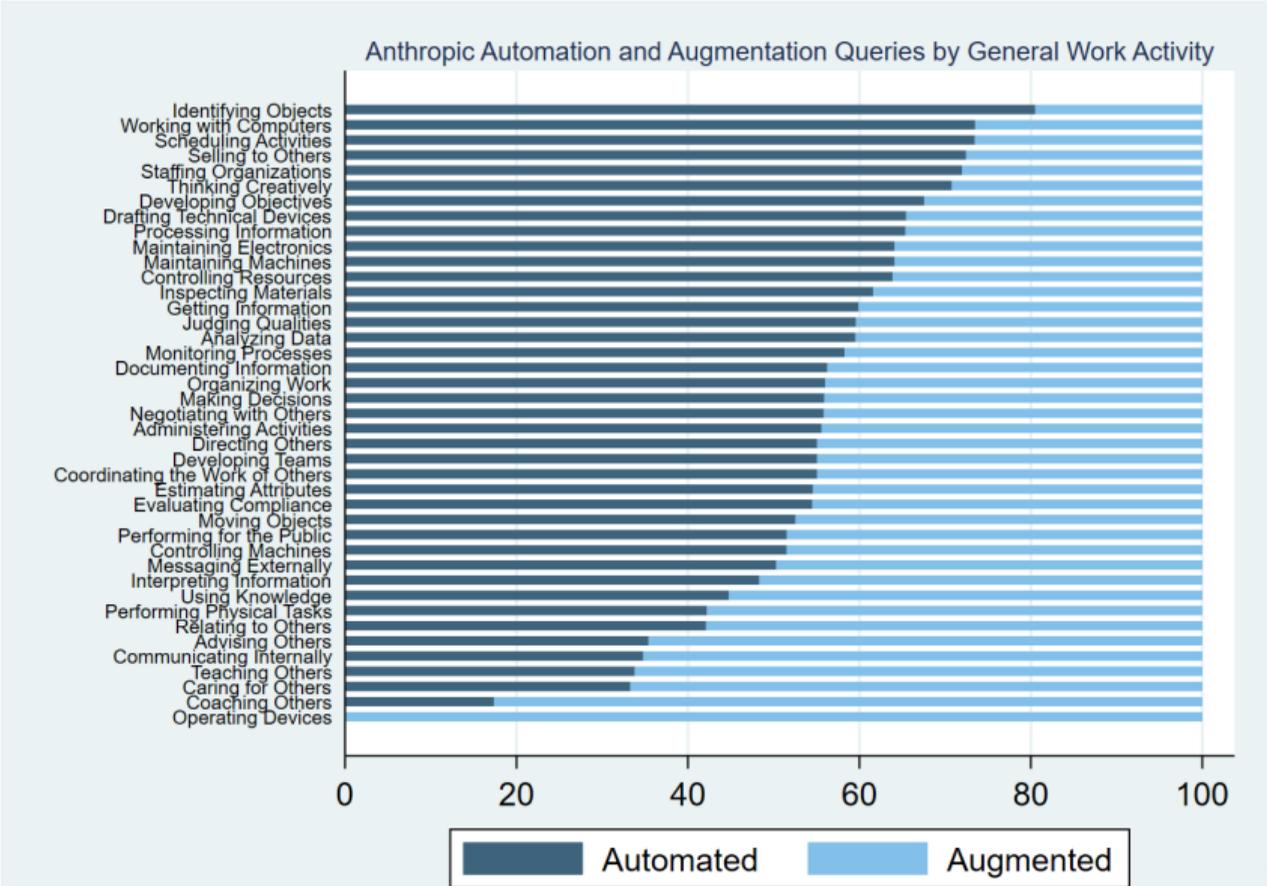
Anthropic Automation and Augmentation Queries by General Work Activity

Outline

Model predictions are re-scaled in SD units
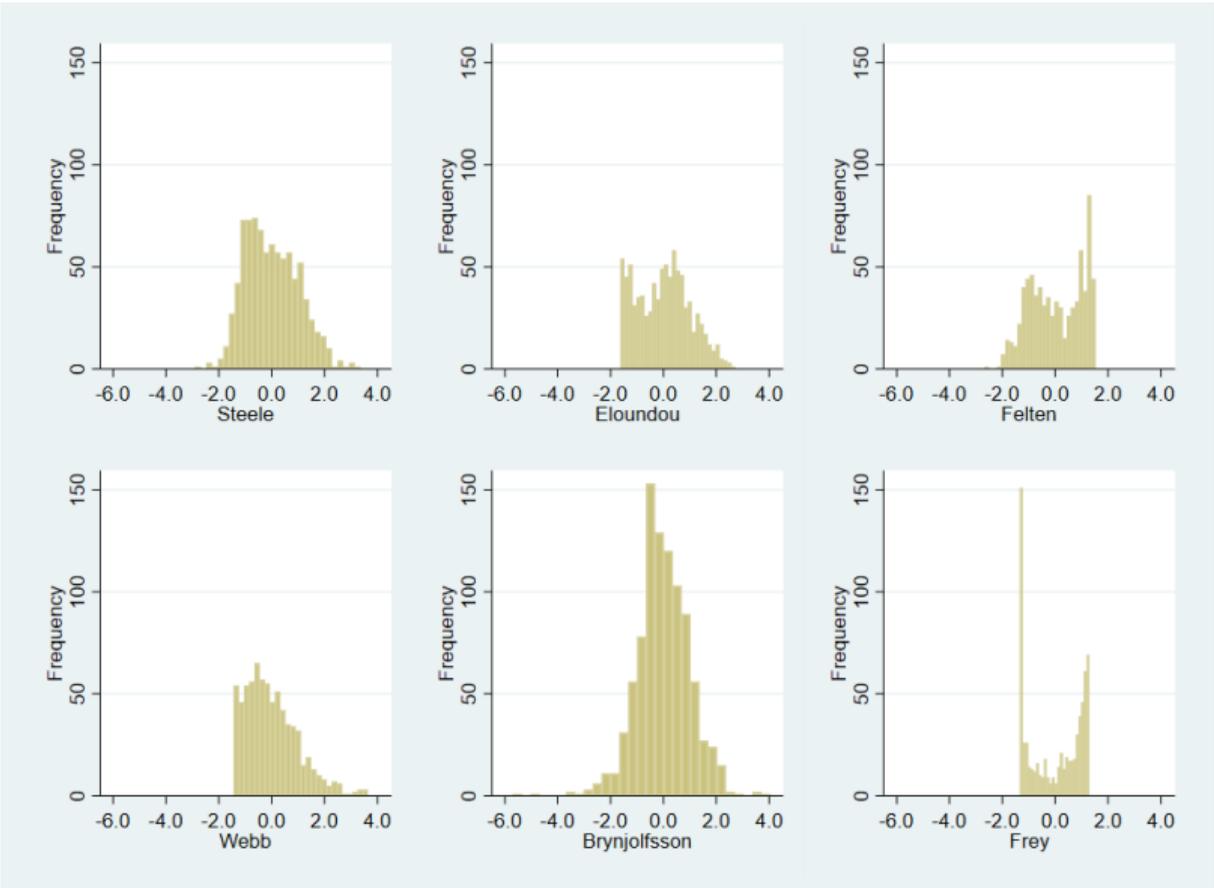
Models yield heterogeneous signals
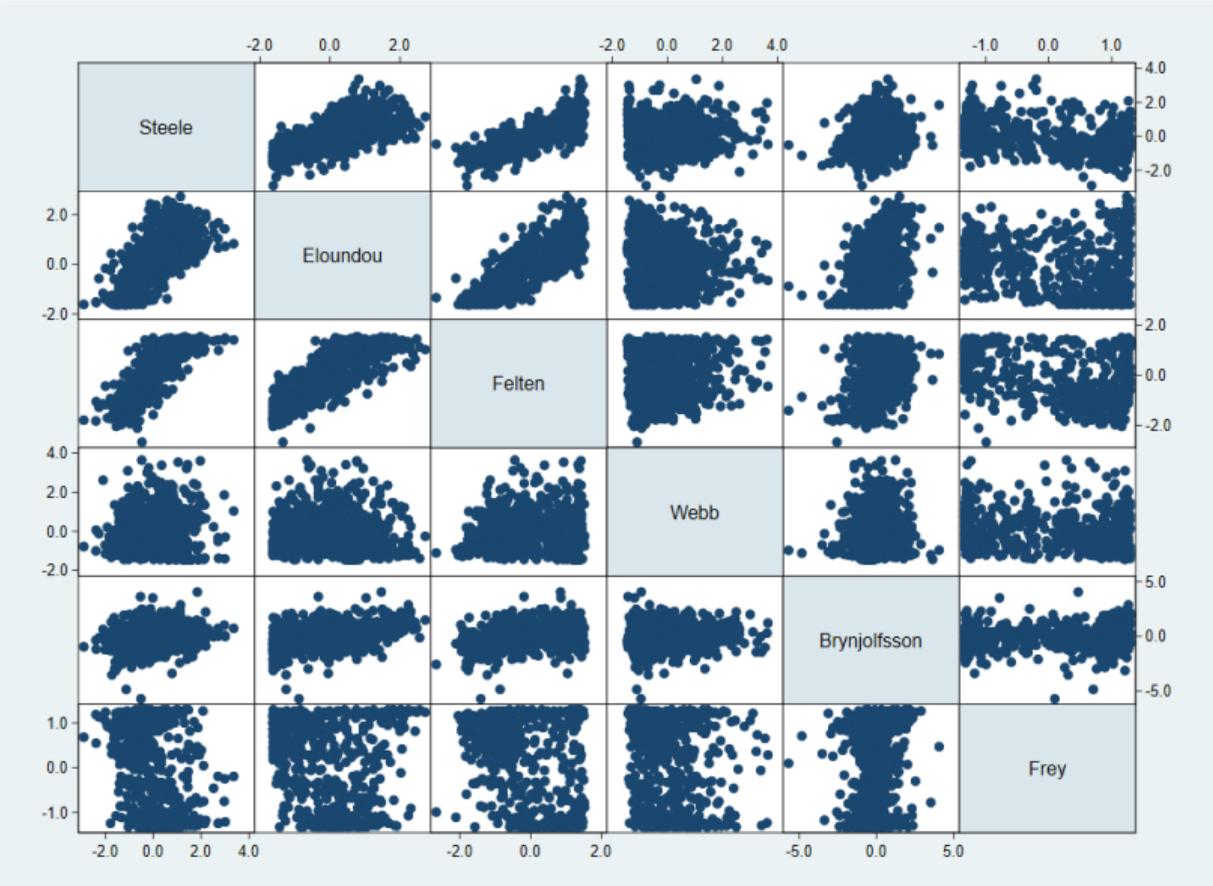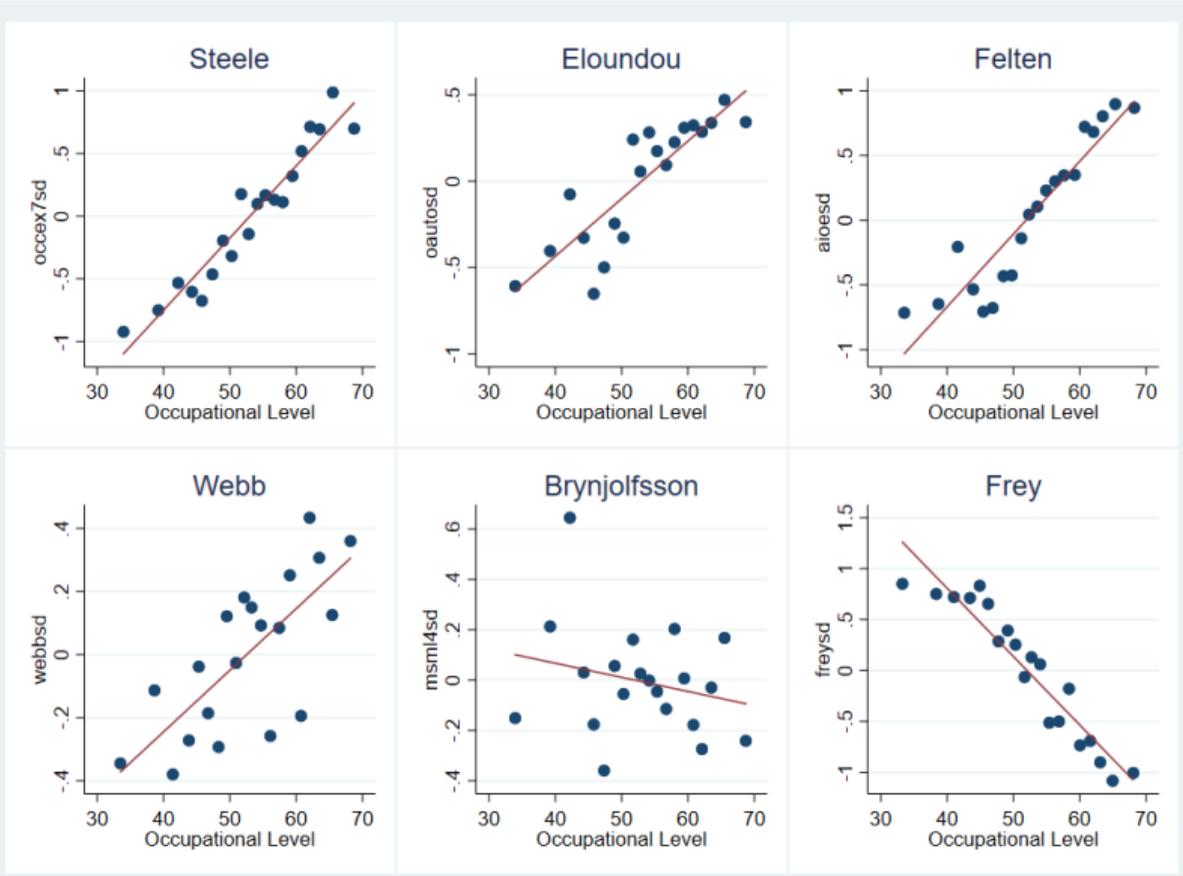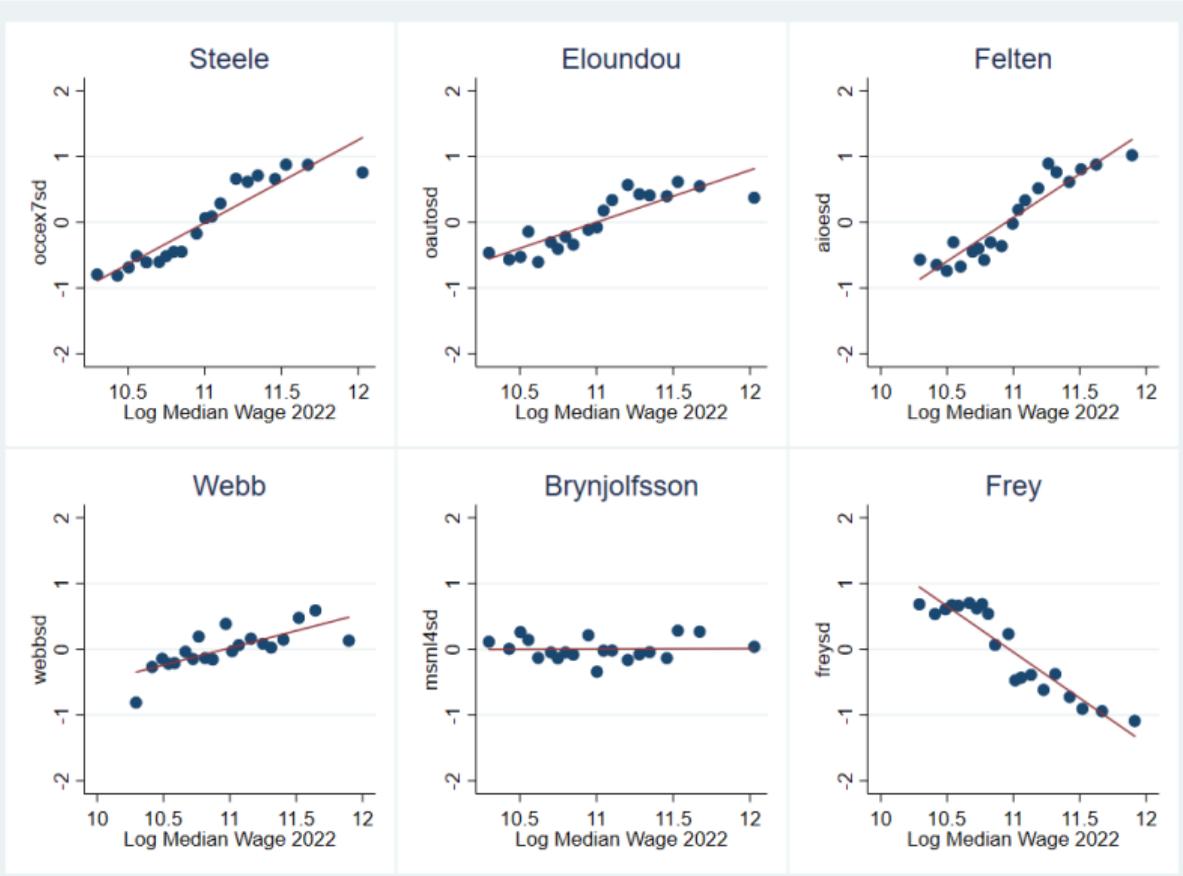
Newer models show exposure rising with occupational level

Newer models show greater exposure at higher salaries

Job category exposure by model

Table 3: Which job categories show greatest exposure, by model?

Model	JobZone	RIASEC	Sector
Steele (Queries)	Adv (0.97)	Investigat (0.99)	Compu/Math (1.6) Legal (1.6)
Eloundou (Possible)	Bach (0.74)	Conventional (53)	Office (1.5) Compu/Math (1.3)
Felten (Crowd)	Adv (0.96)	Investigat (85.7)	Compu/Math (1.4) Legal (1.4)
Webb (Patents)	Bach (0.34)	Investigat (38.8)	Engineer (0.85) Compu/Math (0.77)
Brynjolf (Crowd)	Bach (0.28)	Conventional (66)	Office (1.3) Sales (0.8)
Frey (Theory)	<HS (0.85)	Conventional (67)	Office (0.91) Manufacturing (0.85)

Most-exposed jobs by model

Table 4: Which jobs show the highest automation exposure, by model?

Steele (Queries)	*Eloundou (Possible)*	*Felten (Crowd)*
Environmental Economist	Credit Authorizer	Actuary
Law Clerk	Telemarketer	Financial Examiner
Mathematician	Telephone Operator	Genetic Counselor

Webb (Patents)	*Brynjolf (Crowd)*	*Frey (Theory)*
Civil Engineer Tech	Concierge	Cargo & Freight Agent
Political Scientist	Mechanical Drafter	Data Entry Keyer
Wastewater Plant Oper	Mortician	Insurance Underwriter

Realistic, social, & enterprising: least exposed in 4 recent models
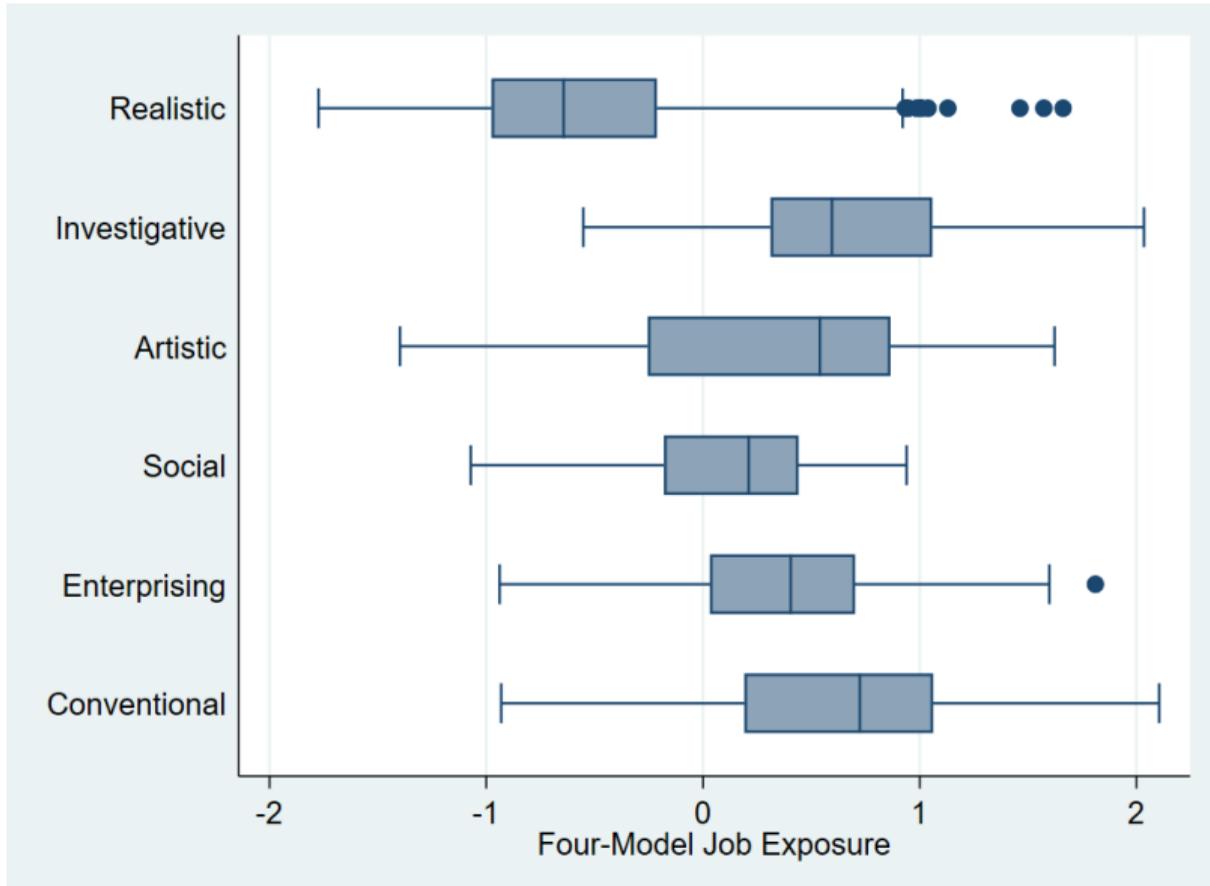
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Summary

1. Automation exposure predictions vary by researcher methods
2. People are using chatbots to code, write, and explain
3. Chatbot use for social job tasks is more augmented than automated
4. Older predictions may under-emphasize scientific and creative exposure
5. Least-exposed across models: realistic, social, & enterprising jobs

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Chatbot *usage* shows high scientific and social exposure

Steele Estimates: Job Exposure by Salary and RIASEC Category
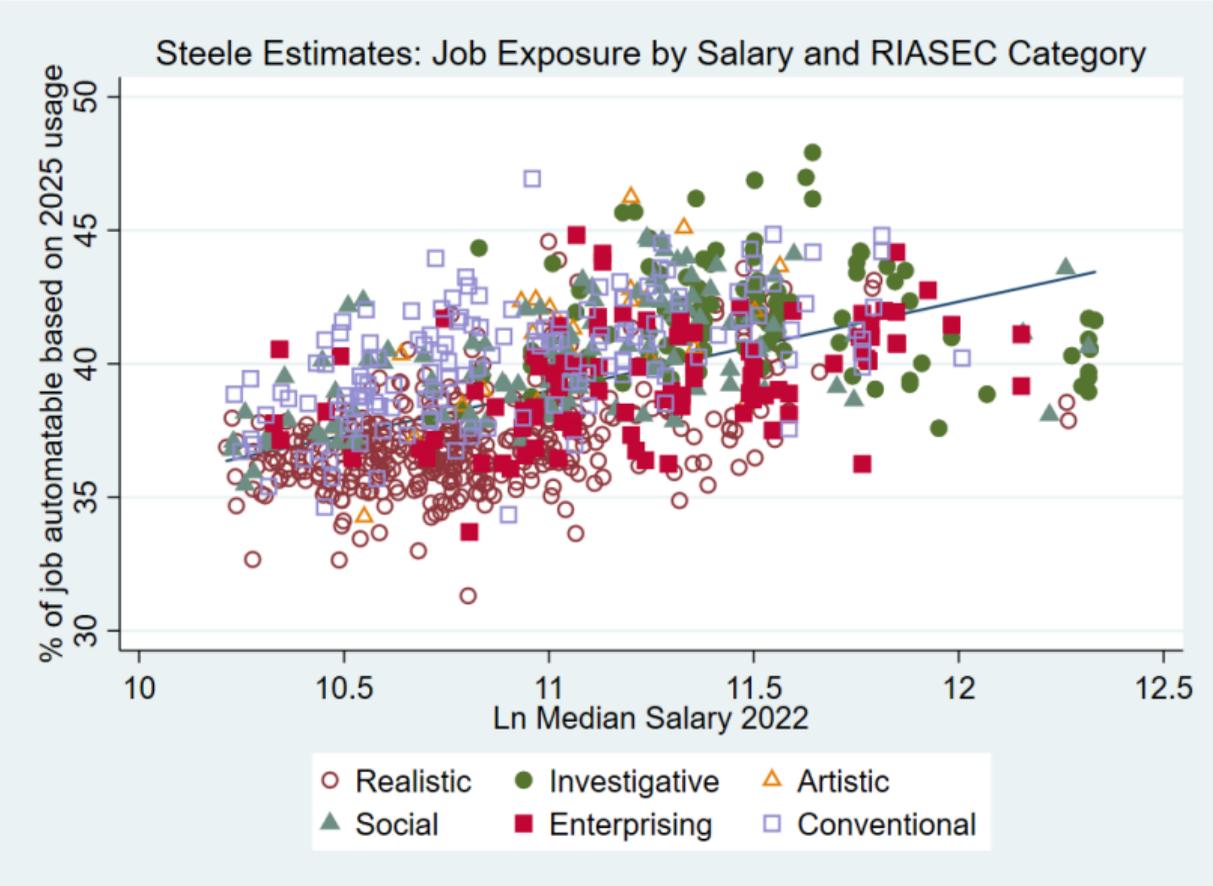
GPT-based automation predictions show high conventional exposure

Eloundou Estimates: GPT-rated for automation exposure

Legend: Realistic, Investigative, Artistic, Social, Enterprising, Conventional

X-axis: Ln Median Salary 2022

Y-axis: % of job automatable based on GPT-4 ratings
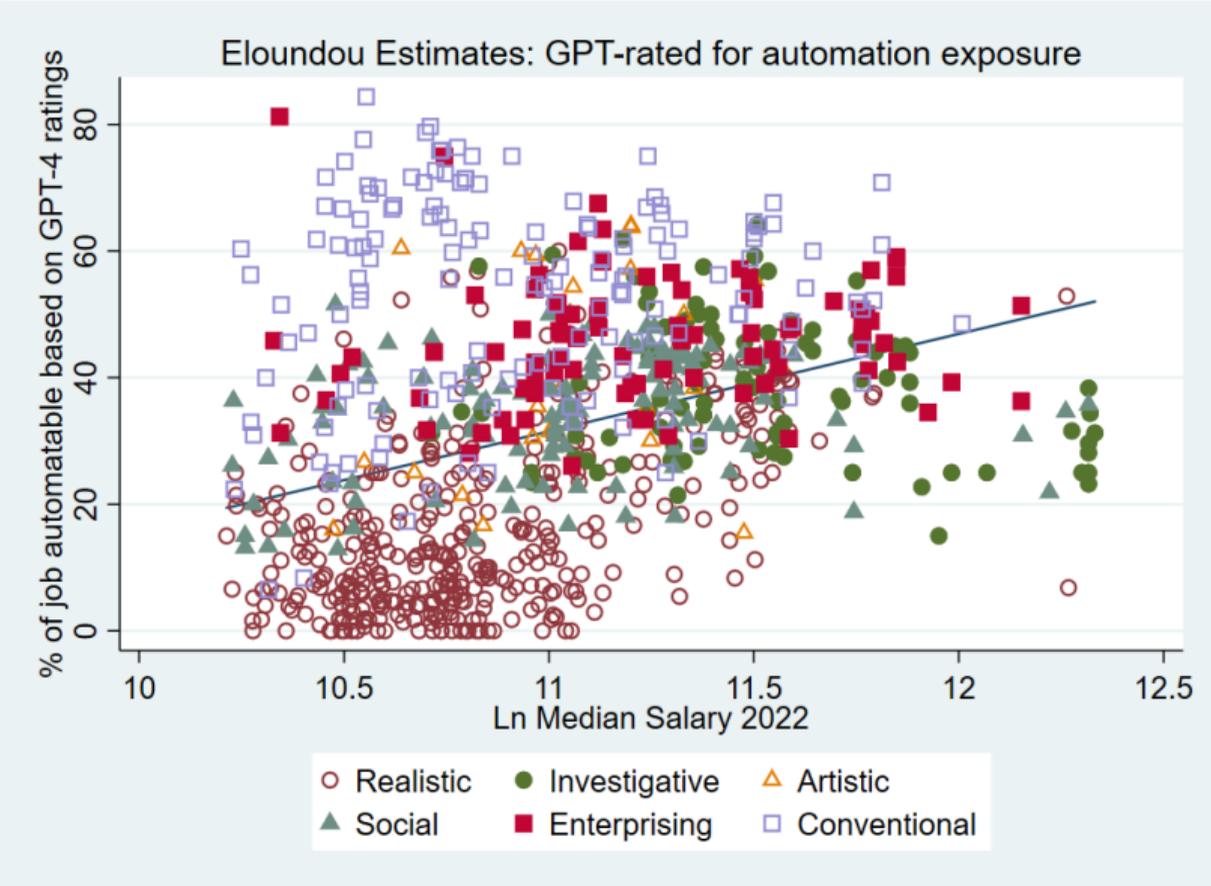
Patents show high exposure for physical and scientific jobs

Webb Estimates: AI patents overlap with job description
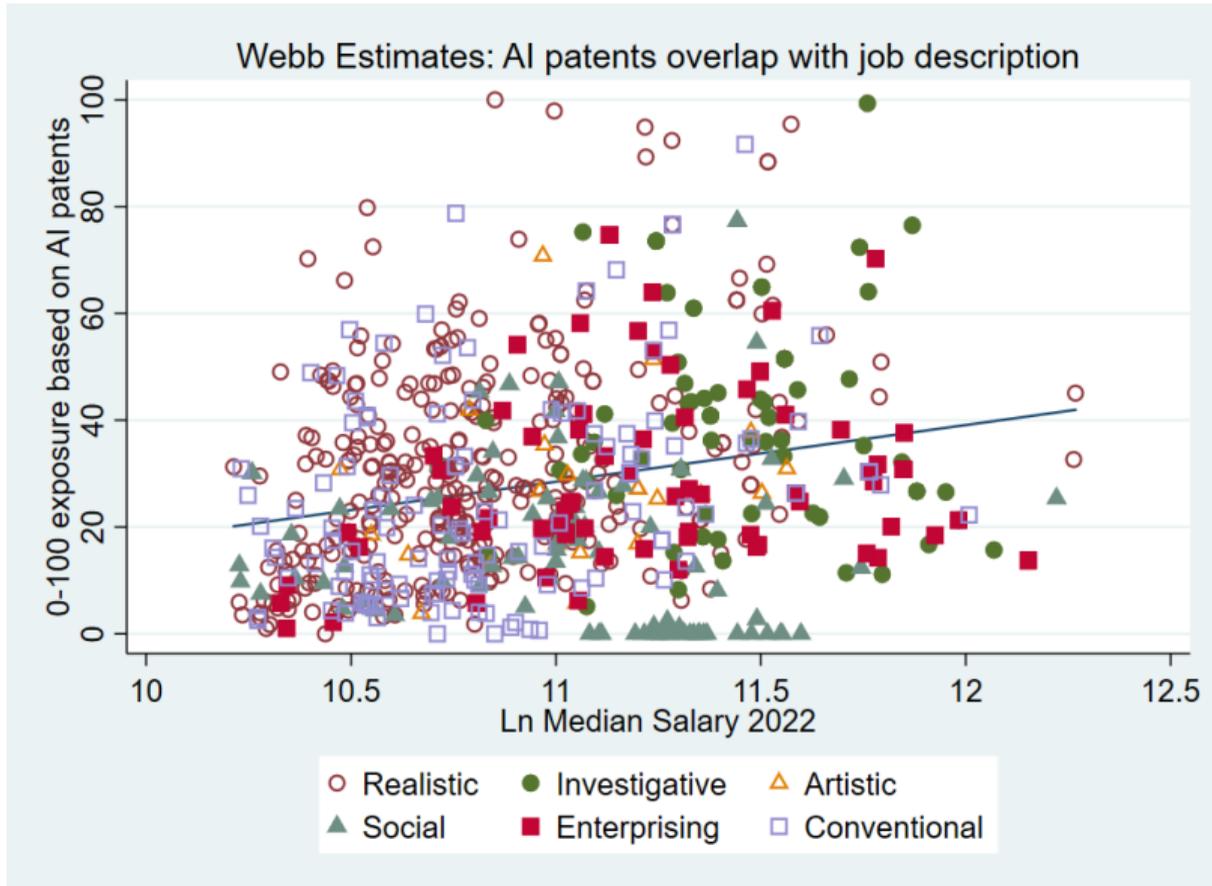
Machine learning estimates show less exposure of high-stakes work

Brynjolfsson Estimates: Suitability for machine learning

Legend:
- ○ Realistic
- ● Investigative
- △ Artistic
- ▲ Social
- ■ Enterprising
- □ Conventional

x-axis: Ln Median Salary 2022

y-axis: 0-100 suitability for machine learning
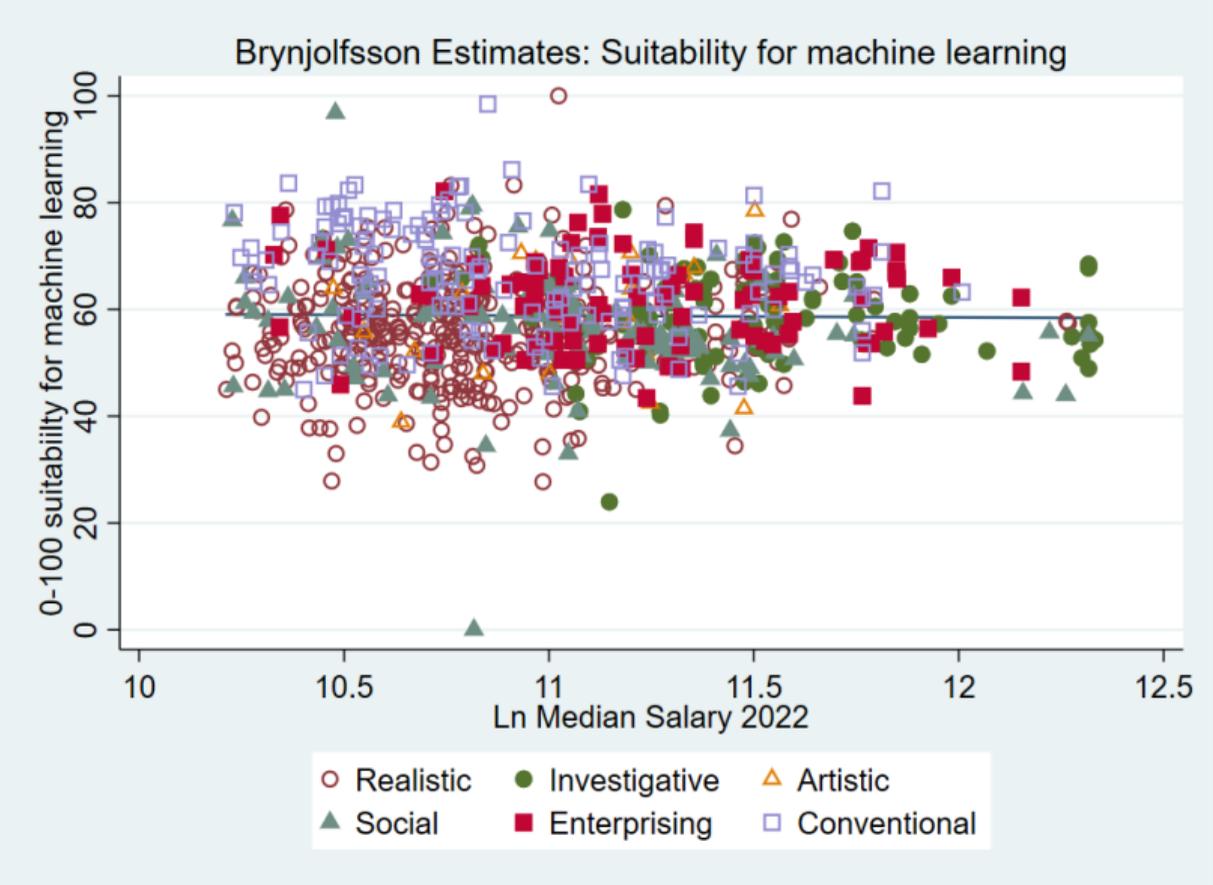
"The Turing Trap" versus "Machines of Loving Grace"

"The distributive effects of AI depend on whether it is primarily used to augment human labor or automate and replace it."
–Erik Brynjolfsson, 2022. The Turing trap. *Daedalus, 151*(2).

"We simply need to break the link between the generation of economic value and self-worth and meaning."
–Dario Amodei, 2026, Jan. The adolescence of technology, essay citing Almodei's 2024 essay, "Machines of loving grace."

The economic payoff of work varies by interest
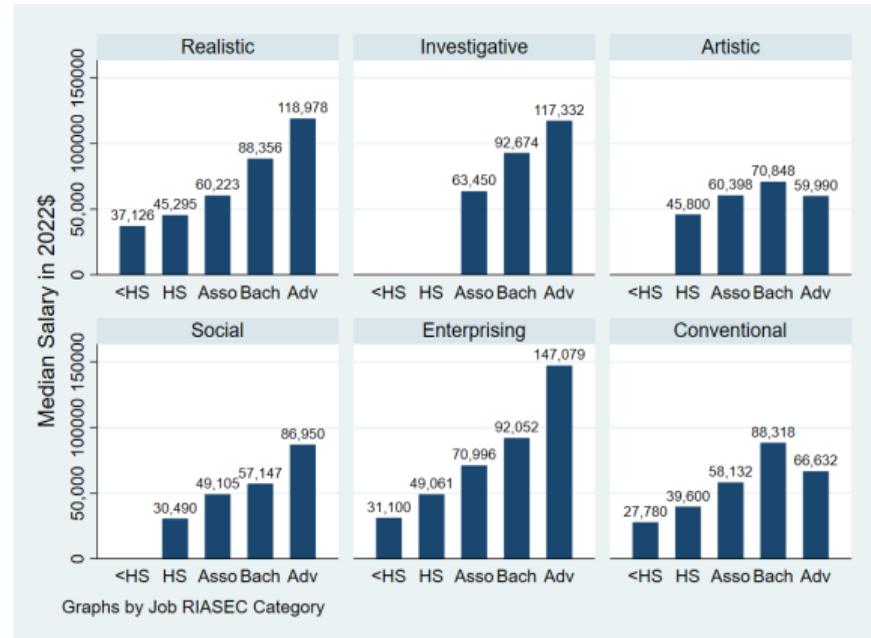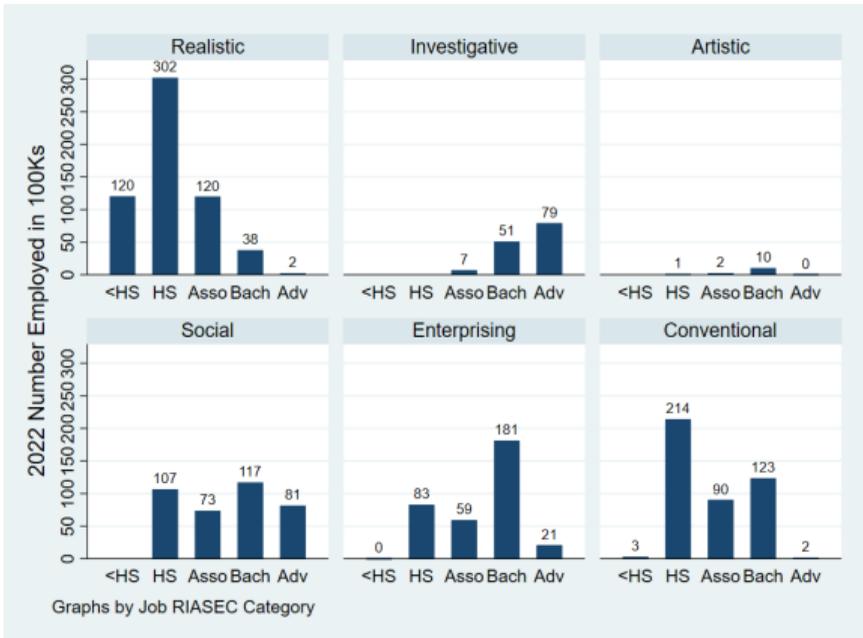
$medsal_j = \alpha + \beta relimportance_g j + \epsilon_j$ where:

- $relimportance_g j$ is relative importance (0-100) of activity category g in occupation j
- $medsal_j$ is median salary of occupation j in 2022\$ in 2022

GWA Salary Differentials Positively Linked to Automation Exposure

Regressing salary differentials on exposure, standardized betas: 0.23, 0.41, & 0.03.
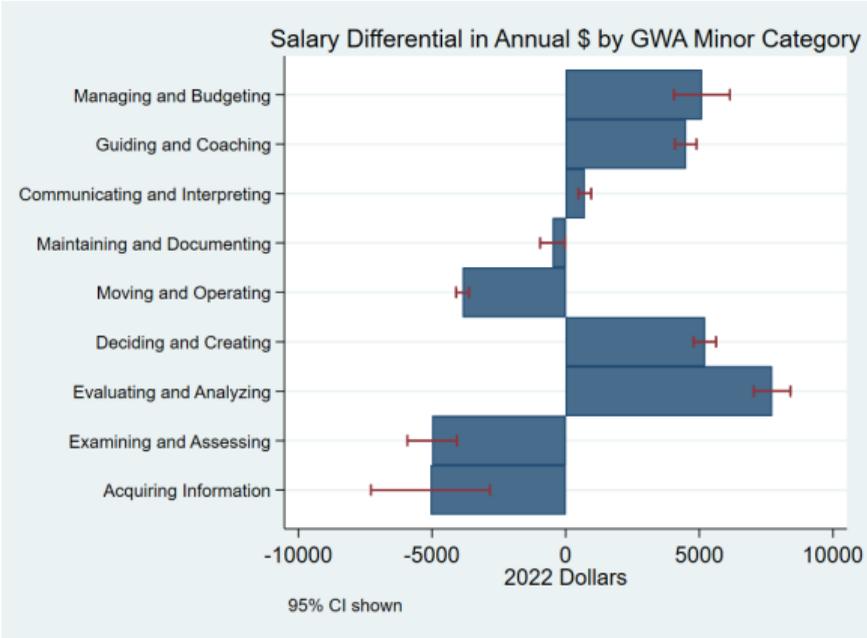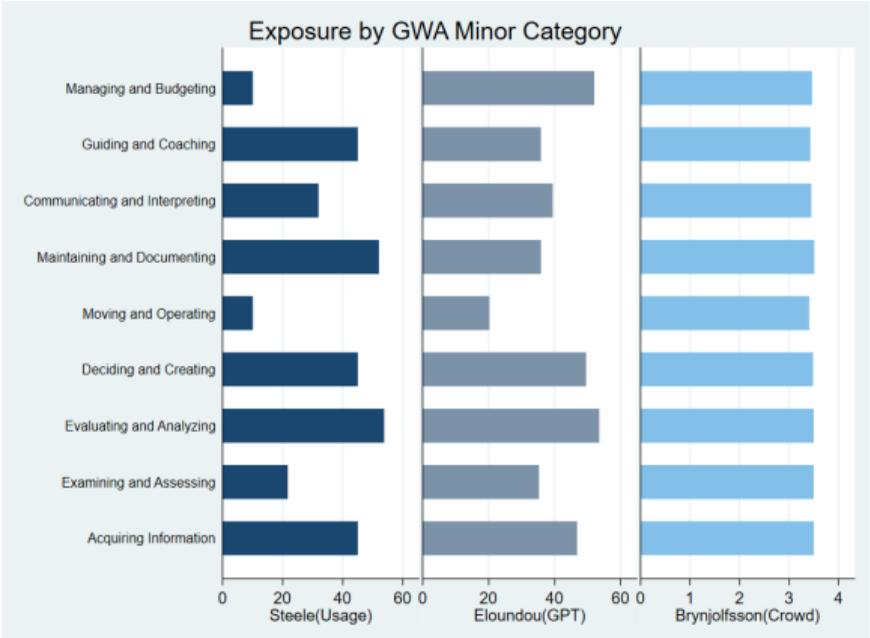
Generalized Work Activity exposure measures vary

Exposure by Generalized Work Activity
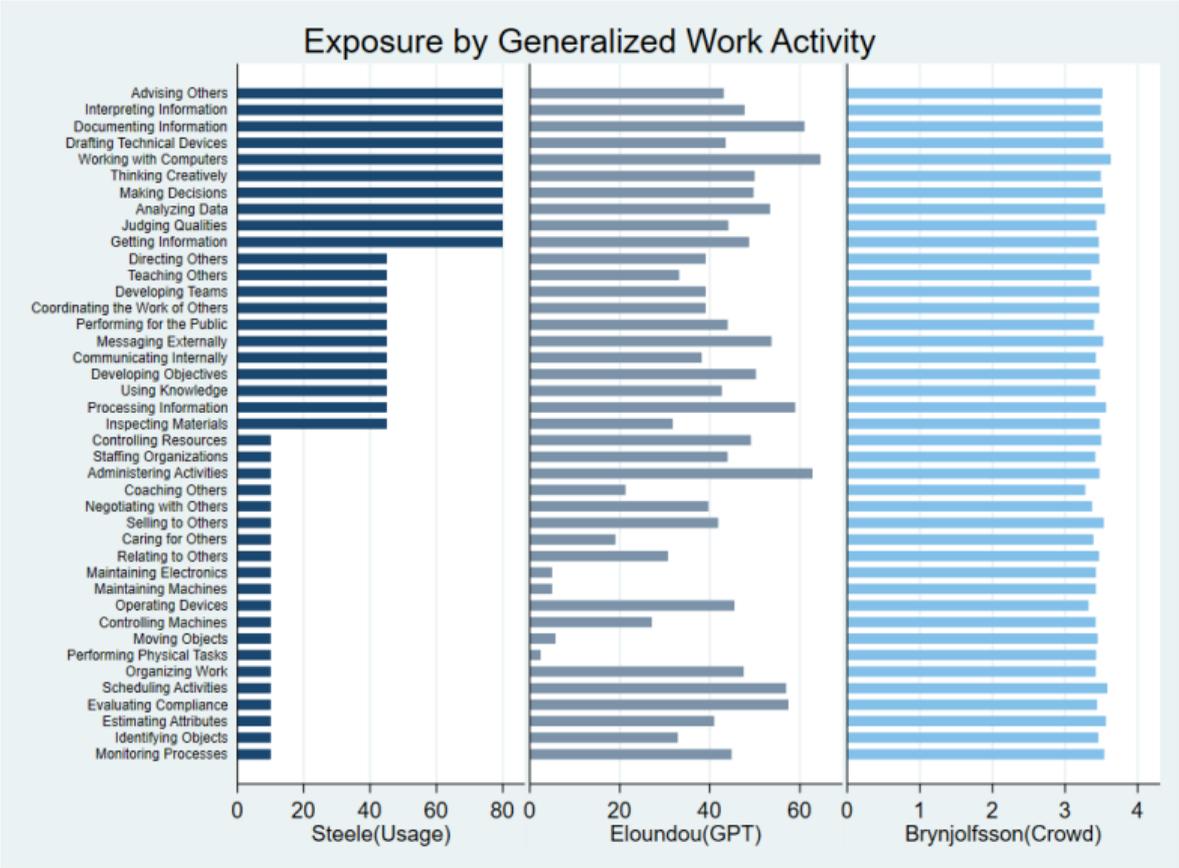
Robustness checks examined

1. Divide by 2 if more than 60% of Claude or 30% of Claude API queries are augmented instead of automated
2. Augmentation exposure: 65, 45, 25, 5 for augmentation percentiles of 90+, 75-90, 50-75, <50
3. Automation exposure: 33, 23, 13, 3 for automation percentiles of 90+, 75-90, 50-75, <50
4. Aggregate 19k task percents to job level, convert to centiles, average Claude and ChatGPT

Is it reasonable to promote augmentation vs. automation?

Table 5: AI as Human Substitute versus Complement

Automation	Augmentation
Automatic Defibrillation	Vital Sign Monitor
Write Your Lit Review	Find and Synthesize New Sources
Build Your App	Expand Your Coding Skills
Grade Student Essays	Generate Rubrics and Grading Templates
Do Your Algebra Homework	Explain Key Algebra Concepts
Conduct Your Data Analyses	Provide Summary Stats & Suggestions
Establish Strategic Priorities	Suggest Priorities to Consider

What may matter for teaching and learning

- College as apprenticeships, with hands-on problem-solving
- Helping students learn *with* the tools (augmented learning)
- Modeling ethical use:
  - Learning, not just submitting
  - Exploring, not just writing
  - Validating, not just building
  - Others...

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