Helping People Choose Careers in the Age of AI

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Outline

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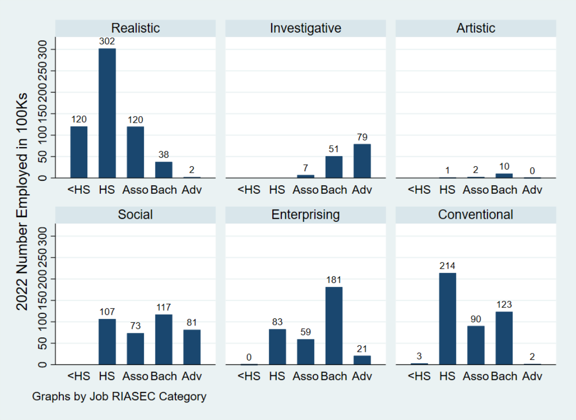
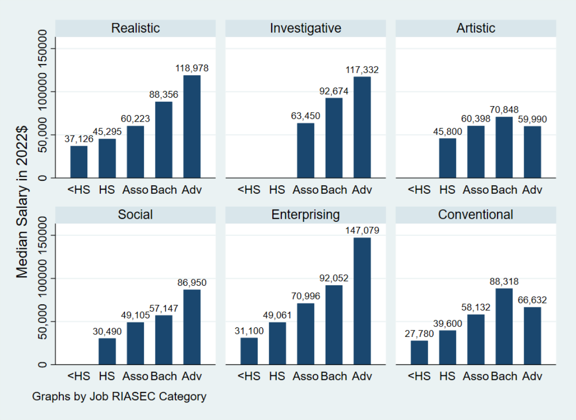
"The Turing Trap" versus "Machines of Loving Grace"

"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."

Indeed, the economic payoff of work varies by interest





Current impact of AI on jobs is uncertain

- Anthropic: 36% of occupations are using AI for at least a quarter of their tasks (Handa et al., 2025)
- Since 2023, freelance job postings in writing and programming (not other fields) dropped 21% (Demirci et al., 2025)
- Since 2023, employment is falling fastest (up to 13%) for early-to-mid-career workers in careers with highest exposure to automation tasks, not augmentation tasks (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, I treat 923 occupations (O*NET SOC Codes) as baskets of about 19,000 tasks, 2,000 Detailed Work Activities, and 41 Generalized Work Activities (GWAs).
2. For GWAs-level aggregates, I weight automation exposure scores by the relative importance of the GWA to the job.
3. I examine economic returns to GWA categories.
4. I examine how my own and 5 other sets of estimates differ by estimation method, job education level, salary, complexity, interest category, and job sector.

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My analysis compares diverse automation prediction models

Table 1: Models Under Consideration

Article	How	Measure
Steele (2026)	Anthropic & GPT queries	% of job tasks automatable
Eloundou et al. (2024)	GPT & human raters	% of job LLM+ can do twice as fast
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 learni (SML)
Frey & Osborne (2017)	Human raters	Abilities that are not social, creative, dexterous

My empirical measure employs 2025 Claude and OpenAI usage

Using query data from 2025 for Appel et al. (2025) and Chatterji et al. (2025), I 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)

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
5. Theory-based exposure estimates at GWA level, adapted from Frey (2017)

Returns to GWA category employ its relative importance across jobs

$medsal_j = \alpha + \beta relimportance_g j + \epsilon_j$ 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

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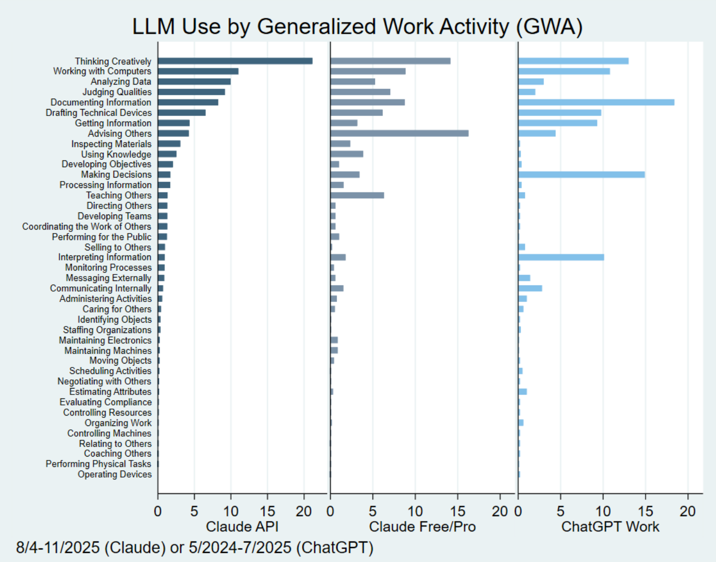
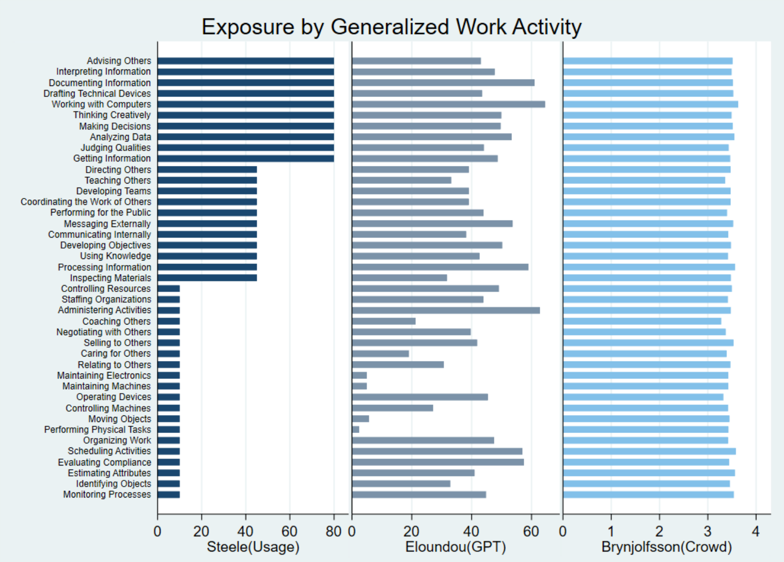
Tasks vary widely in LLM use patterns

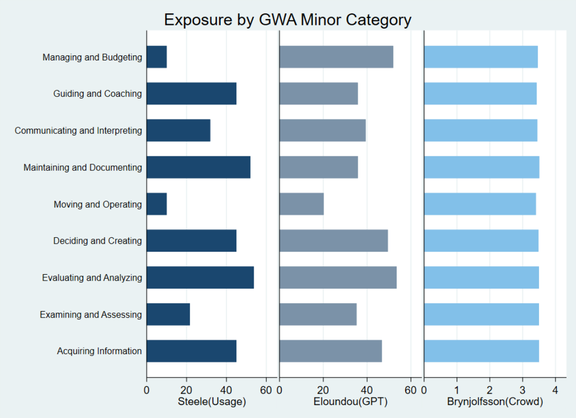


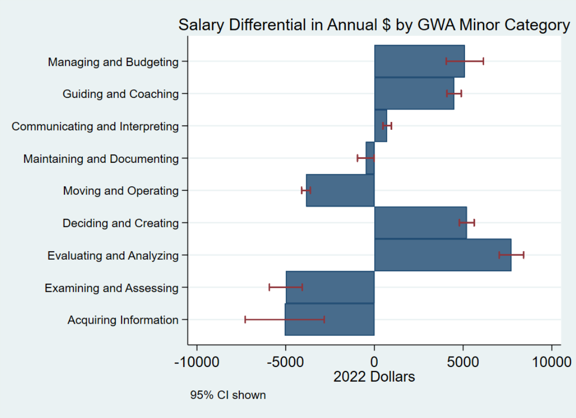
Generalized Work Activity Exposure Measures Vary



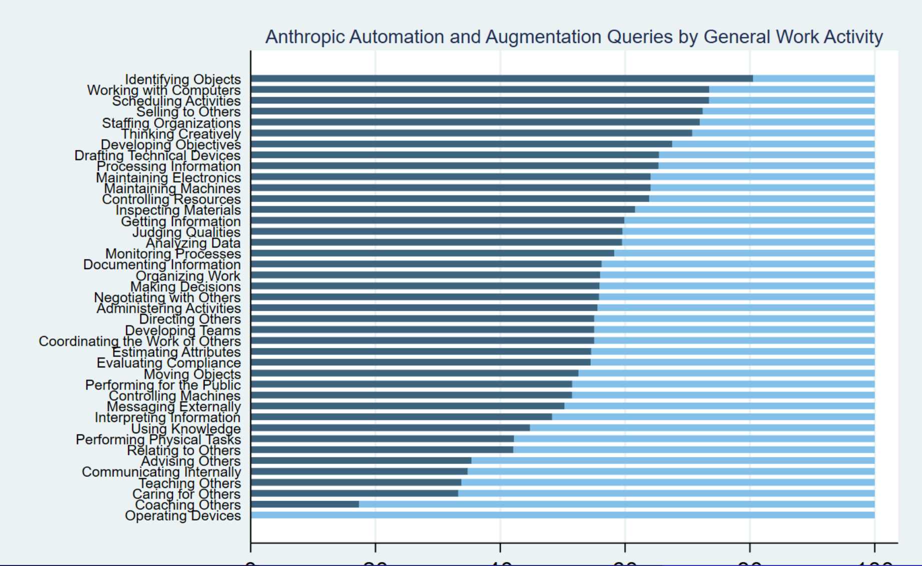
GWA Salary Differentials Positively Linked to Automation Exposure

Regressing salary differentials on exposure, standardized betas: 0.23, 0.41, & 0.03.





GWA augmentation relatively high in coaching, teaching, advising



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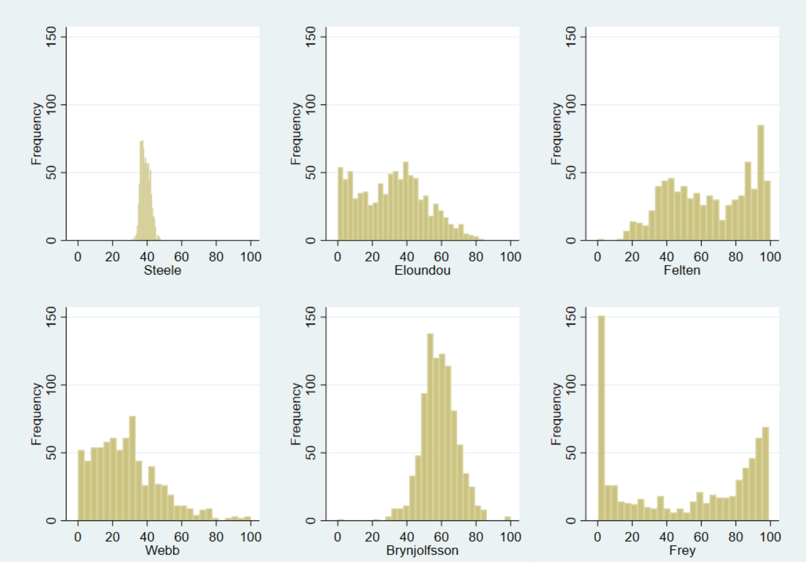
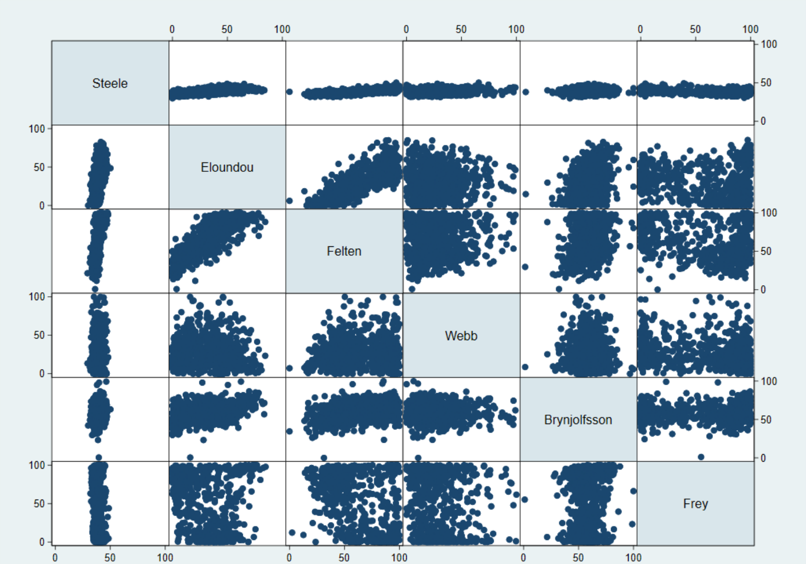
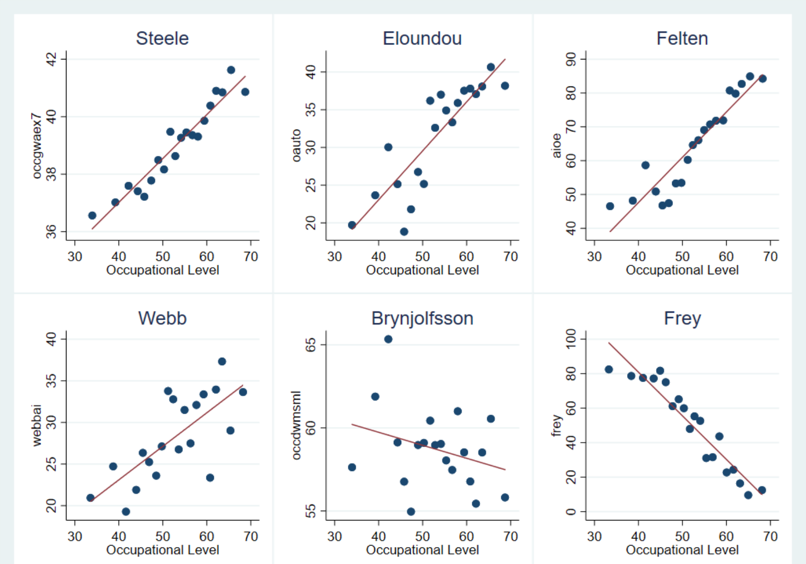
Model predictions are scaled linearly from 0 to 100



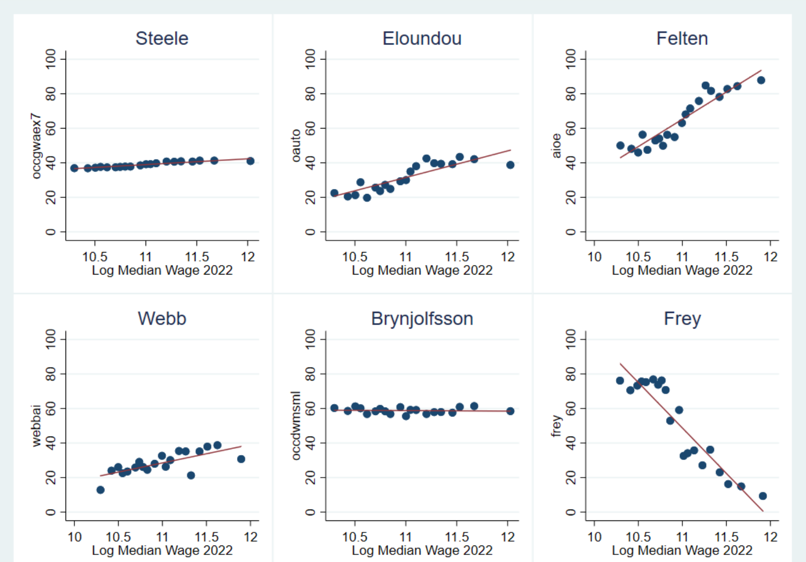
Models yield heterogeneous signals



Models vary in predictions by occupational level



Models vary in predictions by salary



Job category exposure by model

Table 2: Which job categories show greatest exposure, by model?

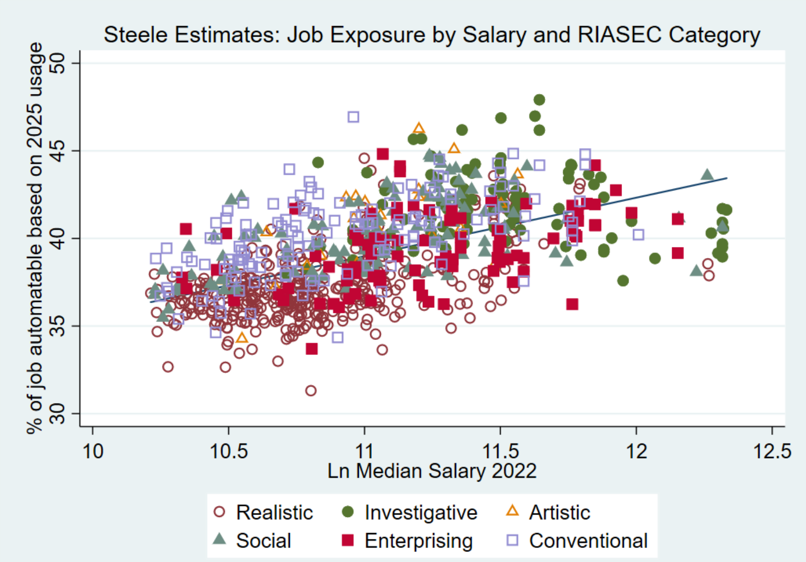
Model	JobZone	RIASEC	Sector
Steele (Queries)	Adv (41.6)	Investigat (41.6)	Compu/Math (43.3) Legal (43.3)
Eloundou (GPT)	Bach (45.9)	Conventional (53)	Office (60.7) Compu/Math (57.6)
Felten (Crowd)	Adv (86.4)	Investigat (85.7)	Compu/Math (97.6) Legal (96.5)
Webb (Patents)	Bach (33.4)	Investigat (38.8)	Compu/Math (45.3) Sciences (45.1)
Brynjolf (Crowd)	Bach (61.6)	Conventional (66)	Office (72) Sales (67.9)
Frey (Theory)	<HS (82.6)	Conventional (67)	Office (84.6) Manufacturing (82.5)

Most-exposed jobs by model

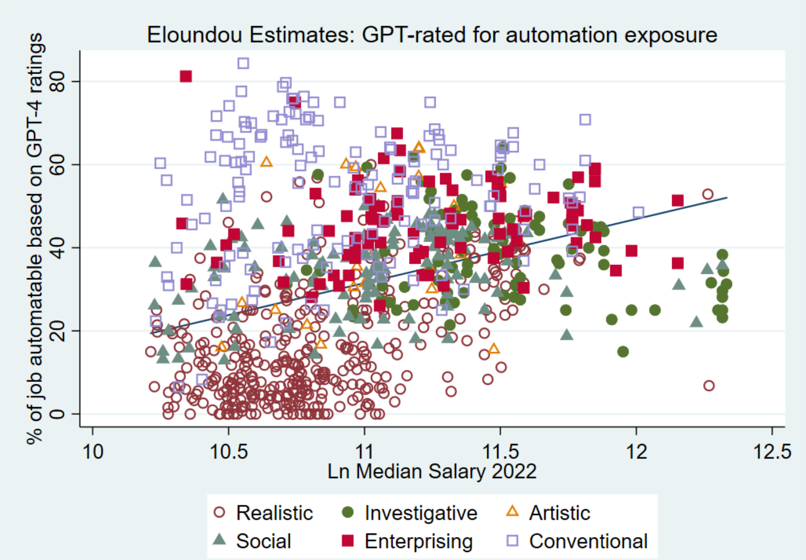
Table 3: Which jobs show the highest automation exposure, by model?

Steele (Queries)	*Eloundou (GPT)*	*Felten (Crowd)*
Environmental Economist	Telemarketer	Genetic Counselor
Mathematician	Credit Authorizer	Financial Examiner
Webb (Patents)	*Brynjolf (Crowd)*	*Frey (Theory)*
Wastewater Treatment	Mechanical Drafter	Telemarketer
Civil Engineer Tech	Mortician	Insurance Underwriter

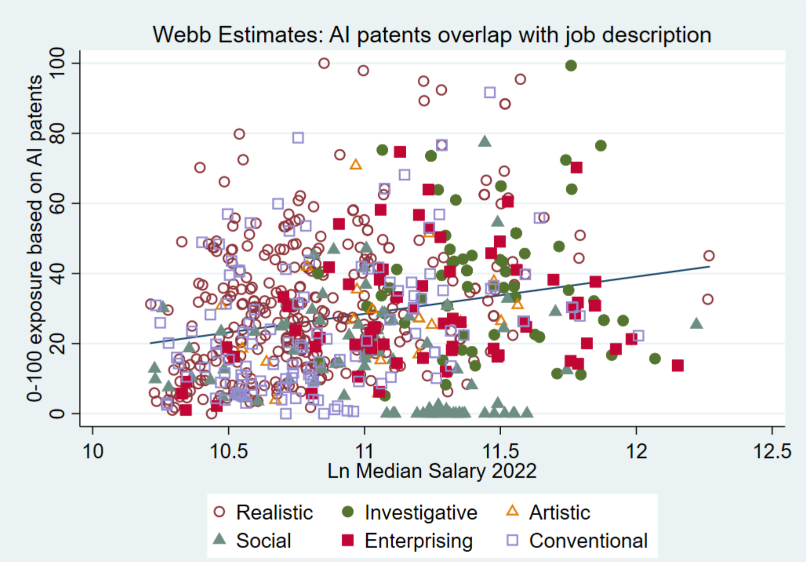
Chatbot usage shows high scientific and social exposure



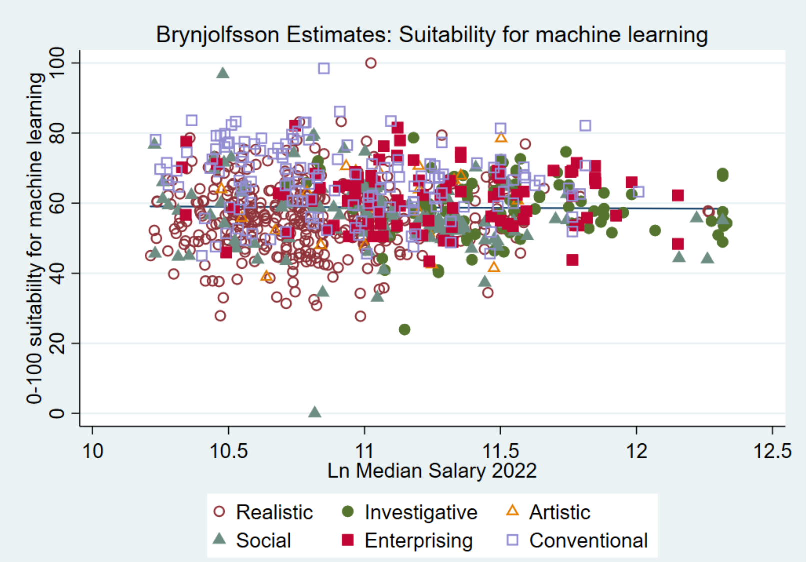
GPT-based automation predictions show high conventional exposure



Patents show high exposure for physical and scientific jobs



Machine learning estimates show less exposure of high-stakes work



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Summary

1. AI automation exposure predictions vary by researcher methods
2. Empirically, people use chatbots to code, write, and explain
3. Patent-based predictions favor robotics and natural sciences
4. Older predictions may under-emphasize scientific and creative exposure
5. Chatbot use for social tasks is more augmented than automated
6. Entrepreneurial and social/helping jobs are less exposed in most models

Is it reasonable to promote augmentation vs. automation?

Table 4: 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

- Hands-on practice so students build expertise
- Helping students learn *with* these tools (augmented learning)
- Modeling ethical use:
    - Learning, not just submitting
    - Exploring, not just writing
    - Validating, not just building
    - Others...

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