From Aspiration to Disillusion?

The Political Consequences of AI Employment Threats

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Outline

Is AI Different From Previous Technologies?

- Technologies produce winners and losers (Gallego and Kurer 2022).
- Robots and computers replace labour in routine manual tasks and complement labour in routine non-manual, penalising unskilled workers while increasing the wage premium for skilled workers.(Goos et al. 2014).
- AI perform cognitive and non-routine tasks, such as data-related skills, calculation, translation, image generation, clerical work and basic research functions, typical of skilled jobs. (Felten et al. 2023).

Which occupations are exposed to AI?

Rank	Most Exposed Occupation	AIOE Score	Least Exposed Occupation	AIOE Score
1	Education managers	1.461	Fitness and recreation instructors	-2.670
2	Psychologists	1.456	House builders	-2.112
3	Financial and insurance branch managers	1.446	Gardeners, horticultural/nursery growers	-1.971
4	Credit and loans officers	1.440	Athletes and sports players	-1.824
5	Transport clerks	1.405	Structural metal preparers/erectors	-1.795
6	Mathematicians, actuaries, statisticians	1.374	Glass and ceramics plant operators	-1.780
7	Personnel clerks	1.353	Bricklayers and related workers	-1.777
8	Vocational education teachers	1.349	Roofers	-1.754
9	University/higher education teachers	1.349	Sweepers and related labourers	-1.753
10	Financial and investment advisers	1.345	Plasterers	-1.715
11	Chemists	1.341	Vehicle cleaners	-1.709
12	Mechanical engineers	1.339	Building construction labourers	-1.648
13	Policy and planning managers	1.334	Mixed crop and livestock farm labourers	-1.630
14	Legislators	1.334	Painters and related workers	-1.623
15	Lawyers	1.329	Floor layers and tile setters	-1.588
16	Insurance representatives	1.327	Building frame/trades workers	-1.565
17	Staff development professionals	1.325	Manufacturing labourers n.e.c.	-1.541
18	Archivists/librarians	1.322	Construction workers n.e.c.	-1.530
19	Social work professionals	1.319	Machine operators n.e.c.	-1.509
20	Management and organization analysts	1.317	Forestry workers	-1.487

Table 1: Top 20 Most and Least AI-Exposed Occupations. AIOE scores by Felten et al. (2021). Exposure is defined as the number of human tasks that AI applications can also perform in a given occupation.

Research Question

- Jobs most exposed to AI require cognitive abilities. Occupations that require problem-solving, logical reasoning, and analytical thinking skills are more susceptible to automation than occupations that rely on physical abilities.
- These jobs are linked to university-level or post-secondary education.
- Yet, while some exposed jobs may be replaced, others can be augmented, depending on how AI will be adopted.
- This is likely to create winners and losers within the same skill group, rather than polarising across the skills' spectrum.

How will AI-driven labour market transformations affect the political attitudes and voting behaviour of the highly educated?

AI and Employment Effects

- **Broad occupational impact.** AI expands the set of automatable tasks, making non-manual, non-routine tasks exposed to automation. (Acemoglu and Restrepo 2019)
- **Task Substitution vs. Complementarity.** Where AI performs tasks at lower cost, labour demand may fall; where AI augments productivity, employment can rise. (Mäkelä and Stephany 2025)
- **Distributional consequences.** The impact varies by skill type rather than skill level. Roles largely demanding general project management, administration and clerical skills may fall in demand vs. specialised AI skills, which may rise in demand (Felten et al. 2021).

AI, Skills, and Employability

- **Labour Market Demand:** Occupations where AI automatable skills are mostly concentrated may decline in demand.
- **Skills Reconfiguration:** Within the same occupation, the task content will evolve, raising returns to adaptable, hybrid, less specific skill sets.
- **Skill sets and Employability:** AI may reduce job opportunities or increase over-qualification and mismatch between skill sets and expected career paths (Ansell and Gingrich 2017).

AI, Education and...Politics

- **AI reshapes employability for graduates:** some fields of study become more vulnerable, while others benefit from AI augmentation.

- **Expectations and Behaviour:** Expectations precede material changes, especially among young people, and shape attitudes and political preferences. (Kurer and Staalduinen 2022)
- **Political implications:** since individuals in higher education link occupational outcomes to effort (Sandel 2021), lower employability expectations fuel:
  - **Perceptions of unfairness:** broken promise of meritocracy
  - **Economic insecurity:** education no longer protects from risk
  - **Political disillusionment:** shift from mainstream to protest voting

Hypotheses

(H1) AI-driven threat to employability → ↓ Fairness Beliefs

(H2) AI-driven threat to employability → ↑ Support for Redistribution

(H3) AI-driven threat to employability → ↑ Left-wing Attitudes

(H4) AI-driven threat to employability → ↑ Support for Challenger Parties

Data and Strategy

- Panel data from the British Election Study Internet Panel (2017-2024, 29 waves).
- Occupational vacancy data from Textkernel–ONS (monthly, January 2017–August 2024).
- New AI exposure indices by occupation (UK-SOC 4-digit) by (Felten et al. 2021; Cazzaniga et al. 2023; Gmyrek et al. 2023).
- New measure of **AI field of education exposure**:
  - Based on 18 different fields of study in higher education.
  - Occupational exposure to AI.
  - Trends in online job posting by split by UK-SOC 4-digit and months.
  - Using ChatGPT's release (Dec 2022) as a shock to job vacancies.

AI-exposed Field-level Employability

- I create a time-invariant vector of predicted probabilities of employment weighted by AI occupational exposure:

$$\hat{\text{Employability}}_i = \sum_{j=1}^{373} \Pr(\text{SOC}_j \mid \text{field}_i, \text{gender}_i \cdot \theta_j \tag{1}$$

- I weight it by the delta of within-occupation vacancies at each time point:

$$\hat{\text{Employability}}_{it} = \left[\sum_{j=1}^{373} \hat{P}_{ij}\right] \times \Delta Vacancies_{jt} \tag{2}$$

- I collapse by field of education:

$$\text{Field Exposure}^{(k)}_{izt} = \frac{1}{N_z} \sum_{i \in z} \left(\hat{\text{Employability}}_{it}\right) \tag{3}$$

Assumptions and Logic

- Individuals select a field of study based on observable trends in labour market demand for different fields of education.
- When ChatGPT is introduced, labour market effects materialise and some occupations become less in demand while others become more in demand.
- Some graduates are more likely than others to be employed in occupations whose demand declines because of their field of study.

Dependent Variables

- **Fairness beliefs**: "Ordinary people do not get their fair share of the nations' wealth". 5 = strongly agree
- **Redistribution**: "The Government should redistribute income from those who are more well-off to those who are less well-off". 5 = strongly agree
- **Left-Right**: 10= Right and 0 = Left
- **Voting Intentions**: "If there were an election tomorrow, which party would you vote for?" Binary indicator

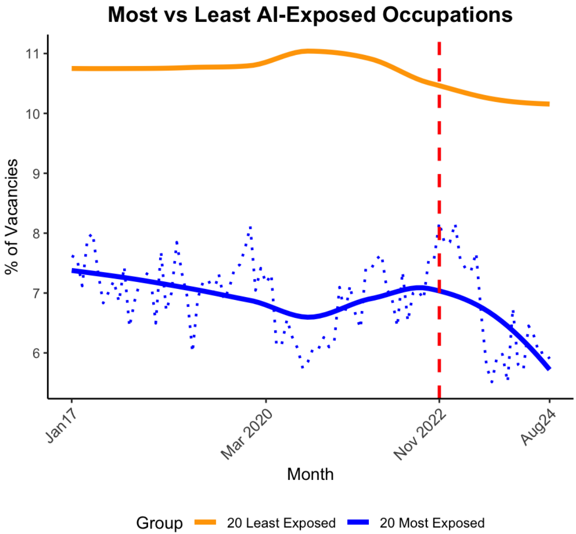

Figure 1: Vacancy trends 2017-2024 for the 20 Most and Least Exposed Occupations. The red dashed line is the launch of ChatGPT in December 2022.

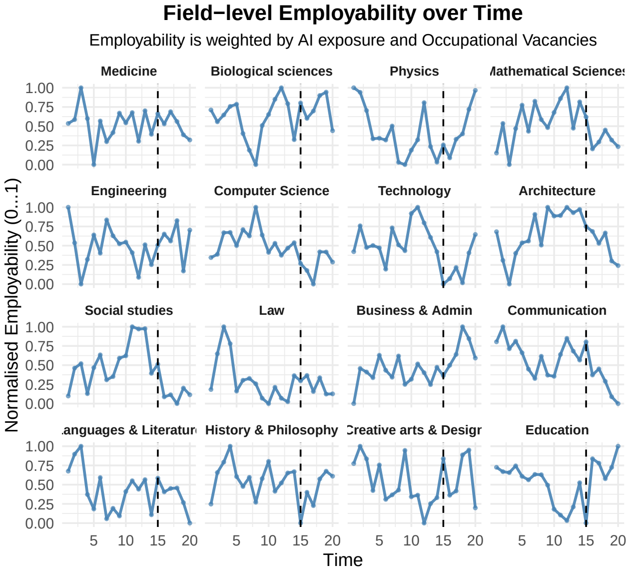

Figure 2: Vacancy-weighted AI Exposure across Different Fields of Higher Education. The dashed line is December 2022.

Did People Know About Chat-GPT Effects?

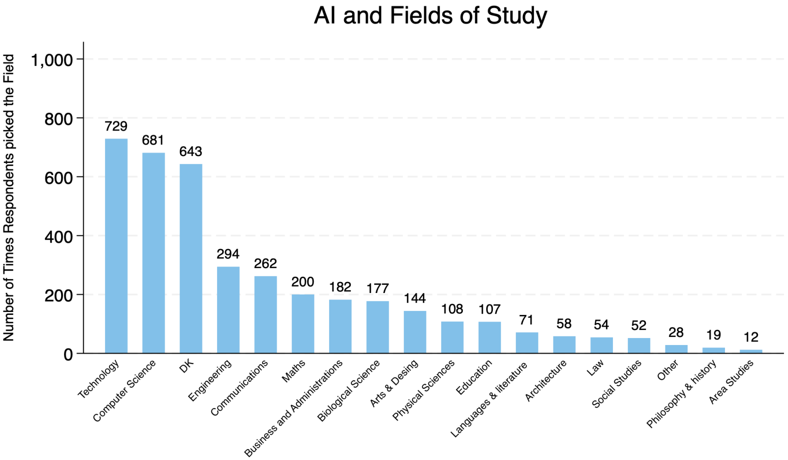

Figure 3: "Which of the following fields of study, if any, do you think will see the highest increase in job opportunities through the use of AI in the field? Please pick up to three." Original Survey

Panel Models: Effect of Field-level AI Exposure

- **Fixed-effects panel models:**
  - Control for unobserved, time-invariant individual traits.
  - Subset by respondents who were currently enrolled in education before December 2022.
  - Estimate within-individual changes in fairness, redistribution, left-right attitudes, and voting intentions.

- **Key assumption:** Students could not anticipate which fields would be most AI-augmented before ChatGPT. Why? Unlike earlier technological innovations, ChatGPT's effects were **highly uncertain:** most people did not know.

Diff-in-Diff with Continuous Treatment

- Estimate the causal effect of AI-driven threats (ChatGPT, Dec 2022) on attitudes and voting intentions.

- **Why Diff-in-Diff?**
  - Panel FE models show over time variation but cannot rule out confounding shocks.
  - A common exogenous event (ChatGPT) creates a natural experiment.
  - Exploits **heterogeneous exposure intensity** across fields of study. No clean control group.

- **Identification:** fields with higher AI exposure should follow similar trends as low-exposure fields, absent ChatGPT; pre-shock vs post-shock divergence measures the causal effect of AI exposure.

$$Y_{it} = \alpha_i + \delta_t + \beta\big(\text{Post}_t \times \text{Exposure}_{z(i)}\big) + \varepsilon_{it}$$

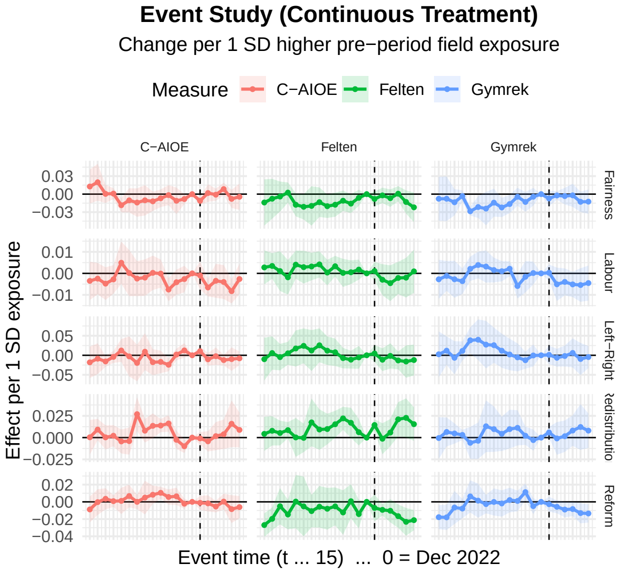

Figure 4: Event Study Analysis of three different operationalisations of AI field exposure on five different outcomes.

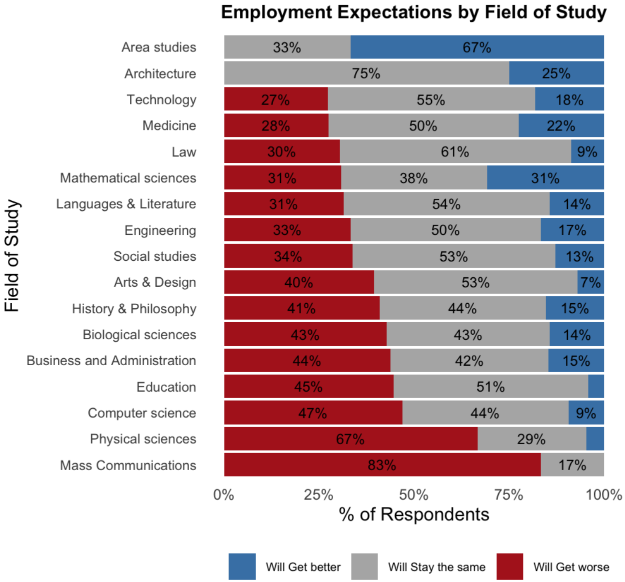

Figure 5: Validation: Do people perceive the threat? Employability Expectations across Different Fields of Higher Education. Original Survey

FE Panel - Attitudinal Models

Table 2: FE regressions on attitudes

	Dependent variable:								
	Fairness Beliefs			Redistribution			Left–Right		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Std Field Exposure1	0.006			0.007			−0.014		
	(0.006)			(0.007)			(0.009)		
Std Field Exposure2		0.011**			0.019***			−0.029***	
		(0.006)			(0.006)			(0.009)	
Std Field Exposure3			0.007			0.014**			−0.020**
			(0.005)			(0.006)			(0.009)
Id FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,640	12,640	12,640	12,433	12,433	12,433	11,741	11,741	11,741
R^2	0.0001	0.0002	0.0001	0.0001	0.0010	0.0004	0.0002	0.0010	0.0003

Note: FE panel regressions with robust standard errors clustered at the individual level.

*p<0.1; **p<0.05; ***p<0.01

FE Panel - Electoral Models

Table 3: FE regressions on Labour and Reform vote

	Dependent variable:					
	Labour (vote_anti_lab)			Reform (vote_anti_ref)		
	(1)	(2)	(3)	(4)	(5)	(6)
Std Field Exposure1	−0.003			0.007		
	(0.003)			(0.007)		
Std Field Exposure2		−0.002			−0.0001	
		(0.003)			(0.003)	
Std Field Exposure3			−0.003			0.003
			(0.003)			(0.006)
Id FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,280	7,280	7,280	2,729	2,729	2,729
R^2	0.0003	0.0001	0.0002	0.0004	0.0000	0.0001

Note: FE panel regressions with robust standard errors clustered at the individual level.
*p<0.1; **p<0.05; ***p<0.01

Attitudinal Models

Table 4: Continuous-treatment DiD regressions on attitudes

	Dependent variable:								
	Redistribution			Fairness			Left–Right		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post × Std Field Exposure 1	0.026*			0.005			−0.043*		
	(0.015)			(0.022)			(0.024)		
Post × Std Field Exposure 2		0.004			−0.017			0.004	
		(0.026)			(0.023)			(0.015)	
Post × Std Field Exposure 3			0.022**			0.011			−0.025
			(0.010)			(0.026)			(0.022)
Observations	12,433	12,433	12,433	12,640	12,640	12,640	11,741	11,741	11,741
R^2	0.730	0.730	0.730	0.658	0.658	0.658	0.784	0.784	0.784
Id FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Continuous-treatment DiD regressions with individual and time fixed effects. Reference period set at December 2022. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

DiD - Electoral Models

Table 5: Continuous-treatment DiD regressions on vote choice

	Dependent variable:					
	Labour (vote_anti_lab)			Reform (vote_anti_ref)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Std Field Exposure 1	−0.012			−0.0005		
	(0.010)			(0.003)		
Post × Std Field Exposure 2		0.010**			−0.002	
		(0.004)			(0.002)	
Post × Std Field Exposure 3			0.003			−0.003
			(0.010)			(0.002)
Observations	11,005	11,005	11,005	11,005	11,005	11,005
R^2	0.650	0.650	0.650	0.367	0.367	0.367
Id FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Continuous-treatment DiD regressions with individual and time fixed effects. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Discussion

- Across models, there is stronger evidence for **increased support for redistribution and left-wing economic attitudes** among graduates. Resonance with automation risk literature (Thewissen and Rueda 2019).

- In Panel models, unfairness perceptions also increase. Possible resonance with the literature on status anxiety (Gidron and Hall 2017).

- Electoral effects are weak. Partial evidence that exposure among graduates drives **support for the Labour Party** but not Reform. Resonance with anti-incumbent voting literature more than far-right voting (Van Overbeke 2024).

Contributions

- New measure and evidence on the potential of AI to polarise the educational group of the highly educated, so far linked to progressive politics and not to redistribution support.
- General leftward shift among graduates with lower employment prospects.
- AI may drive anti-incumbent voting. Will, in the long run, pessimistic expectations shift graduates to the radical right alongside distrust towards the economic system?

Thank you!

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