

ICM 2026 Problem F: To Gen-AI, or Not To Gen-AI?

A data-informed model of GenAI exposure and institution-specific educational recommendations

Team #----

Summary Sheet

- **Careers + institutions.** Software Developers (SDSU), Electricians (LATTC), Writers & Authors (Academy of Art). National results use employment-weighted SOC bundles (Table 8).
- **Data & audit.** BLS OEWS + EP + O*NET; independent reality-check vs AIOE: $r = 0.942$, $\rho = 0.938$ (Table 12).
- **Model (1 line).** $\text{NetRisk} = \frac{\text{Writing+ToolTech}}{2} - \frac{\text{Physical+Social+Creativity}}{3}$; define $s_{\text{comp}} := m_i s$ with $m_i \leq m_{\max} = 0.2$, then $g_{\text{adj}} = g_{\text{base}} - s \max(\text{NetRisk}, 0) + s_{\text{comp}} \max(-\text{NetRisk}, 0)$. **Projections use calibrated NetRisk when available.**
- **Headline findings (national 2034; SOC bundles).** Under immediate High disruption vs. baseline, employment shifts by: Software Developers ($2,075,300 \rightarrow 1,490,209$) ($-585,091$), Electricians ($962,800 \rightarrow 964,621$) ($+1,821$), Writers and Authors ($313,700 \rightarrow 249,054$) ($-64,646$). Ramp adoption reduces the magnitude of disruption: Software Developers ($2,075,300 \rightarrow 1,789,549$) ($-285,751$), Electricians ($962,800 \rightarrow 963,619$) ($+819$), Writers and Authors ($313,700 \rightarrow 282,882$) ($-30,818$) (Table 8).
- **Recommendations.** SDSU CS: maintain/slight growth; LATTC Electric: grow capacity; Academy of Art Writing: consolidate/specialize toward higher-originality niches and editing/production workflows (Section 5).
- **Limitations.** Scenarios treat s as a transparent stress-test knob (not a causal estimate); careers are small SOC bundles; local sizing uses scaled openings as a proxy (Section 4.4).

Artifacts: `scenario_summary.csv` (sha256:15fdeed5ddec), built 2026-02-01 20:32 UTC

Contents

1 Problem framing and choices	3
2 Data and preprocessing	3
2.1 BLS OEWS (local labor market context)	3
2.2 BLS Employment Projections (national baseline trend)	3
2.3 O*NET mechanism layer (why substitution vs. complementarity)	3
2.4 Crosswalks and coverage (what gets dropped)	3
3 Model	4
3.1 Mechanism dimensions	4
3.2 Net Risk index	4
3.3 External calibration to AI applicability	5
3.4 Scenario employment projection	7
3.5 Definitions & Provenance (auditability)	10
4 Results	10
4.1 National outcomes for the three careers	10
4.2 Dynamic Adoption	11
4.3 Job openings and program sizing	11
4.4 Sensitivity and sanity checks	12
4.4.1 Mechanism Layer Stability	12
4.4.2 Calibration Validation	12
4.4.3 External benchmark reality check	13
4.4.4 Scenario and Parameter Sensitivity	14
4.4.5 Local openings scaling robustness	16
5 Institution-specific recommendations	17
5.1 SDSU (Software Developers)	18
5.2 LATTC (Electricians)	18
5.3 Academy of Art University (Writers and Authors)	19
5.3.1 Transition Plan	19
6 Beyond employability: other success metrics	20
7 Generalization	22
8 Prompt coverage checklist	22
A Mechanism Layer Details	25

1 Problem framing and choices

We aim to advise leaders of three post-secondary programs on how to address GenAI, using an auditable model grounded in public labor-market data and an explainable O*NET mechanism layer. Our framing follows tasks-based technology theories: GenAI can substitute for some language/cognitive tasks while complementing others, changing task composition and productivity rather than deterministically eliminating whole occupations [3, 7, 1]. We choose the three careers to match the prompt’s STEM/trade/arts categories and to span a wide range of task structures (software = tool/knowledge work; electricians = physical/manual, onsite; writers = writing-intensive creative production).

2 Data and preprocessing

2.1 BLS OEWS (local labor market context)

OEWS provides local (state and metropolitan) employment and wage levels for occupations. We use these as the institution-specific context inputs: the ‘local’ employment level and wages for each program’s regional labor market [10].

2.2 BLS Employment Projections (national baseline trend)

EP provides national occupational employment projections over 2024–2034, which we convert to an annual baseline growth rate g_{base} . National trajectories use EP (all jobs) for consistency with baseline growth rates; OEWS (wage-and-salary) is used for local labor-market context. We use EP as the no-GenAI baseline trajectory for each focal career (aggregating across the SOCs in its bundle) [9].

2.3 O*NET mechanism layer (why substitution vs. complementarity)

We use O*NET 30.1 ‘Importance’ ratings from Work Activities, Abilities, and Skills to construct five dimensions. We compute each dimension score per occupation and convert to a percentile across occupations (0–1). This produces interpretable inputs for NetRisk [4, 6, 5].

Attribution. O*NET® data used under the O*NET Database Content License; see References [5].

2.4 Crosswalks and coverage (what gets dropped)

Occupational taxonomies differ between OEWS/EP (SOC-based) and O*NET (O*NET-SOC). We align them at the SOC occupation code level used in BLS tables by slicing O*NET-SOC codes (e.g., 15-1252.00) to their 7-character SOC stem (e.g., 15-1252). This merges multiple O*NET-SOC specialties into one SOC occupation, which is appropriate because BLS publishes OEWS/EP at the SOC level.

Not every SOC appears in every data source: some SOC codes present in O*NET do not appear in OEWS or EP tables (and vice versa), and some are aggregation/detail differences. Table 1 reports counts at each stage (O*NET-SOC → SOC slice → relevant elements → mechanism-scored occupations → overlap with OEWS/EP) so that any ‘dropped’ occupations are transparent and auditable.

Table 1: Coverage and mapping audit: O*NET → SOC → scored mechanism layer → BLS tables.

Quantity	Count
O*NET-SOC codes in loaded O*NET files (IM scale)	894
Unique SOC (7-char slice) in loaded O*NET files	774
SOC with at least one relevant element for our 5 dimensions	774
SOC with mechanism scores written to <code>mechanism_layer_all.csv</code>	774
Unique occupations in OEWS national table	1,396
Unique occupations in EP baseline table	1,112
SOC present in both mechanism layer and OEWS national	750
SOC present in both mechanism layer and EP baseline	751
SOC present in mechanism layer, OEWS, and EP	750

3 Model

3.1 Mechanism dimensions

Let $d \in \{\text{Writing, ToolTech, Physical, Social, Creativity}\}$ be the five dimensions. For each occupation i , we compute a raw mean importance score from selected O*NET elements, then convert to a percentile across the occupation set:

$$x_{i,d} \in [0, 1] \quad (\text{percentile among occupations}).$$

3.2 Net Risk index

Define substitution and defense scores:

$$\text{Sub}_i = \frac{x_{i,\text{Writing}} + x_{i,\text{ToolTech}}}{2}, \quad \text{Def}_i = \frac{x_{i,\text{Physical}} + x_{i,\text{Social}} + x_{i,\text{Creativity}}}{3},$$

and $\text{NetRisk}_i = \text{Sub}_i - \text{Def}_i$. Positive NetRisk implies higher exposure to substitution; negative NetRisk implies relative sheltering/complementarity.

Table 2 provides summary statistics for the NetRisk distribution across all scored occupations, and the interpretation examples below illustrates the interpretation by listing extreme examples from both tails of the distribution.

Table 2: Summary statistics for NetRisk scores (from `data/mechanism_risk_scored.csv`).

Statistic	Value
Mean	0.000
Std. Dev.	0.521
10th percentile	-0.679
50th percentile (median)	-0.044
90th percentile	0.714

Extreme Positive Tail (Most Exposed):

- Actuaries (15-2011): NetRisk = 1.000

- Data Scientists (15-2051): NetRisk = 0.986
- Economists (19-3011): NetRisk = 0.983

Extreme Negative Tail (Most Sheltered):

- Manufactured Building and Mobile Home Installers (49-9095): NetRisk = -0.962
- Helpers–Extraction Workers (47-5081): NetRisk = -0.934
- Roof Bolters, Mining (47-5043): NetRisk = -0.914

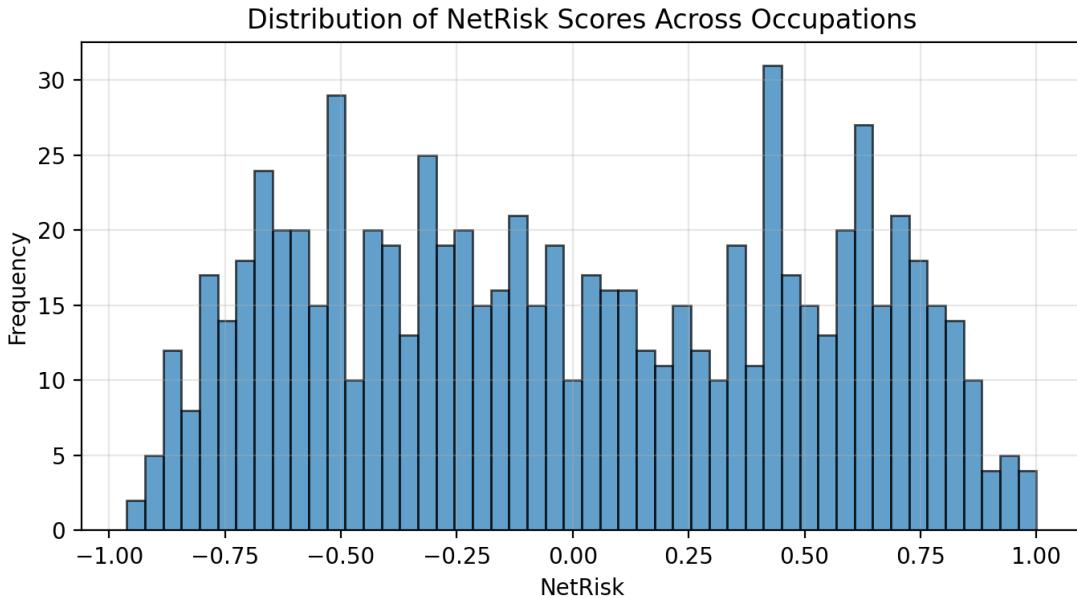


Figure 1: Distribution of NetRisk scores across all occupations in the mechanism layer (from `data/mechanism_risk_scored.csv`).

3.3 External calibration to AI applicability

To improve rigor, we calibrate the mechanism weights against an external occupation-level AI applicability measure from the *Working with AI* dataset (Tomlinson et al., 2025), which provides SOC-level applicability scores derived from real-world GenAI usage patterns [8]. We fit nonnegative weights on the five dimensions with defense dimensions entering with negative sign. Because the five dimensions are correlated, the nonnegativity constraint can yield sparse solutions (some weights at or near zero), which should be interpreted as “adds little predictive power given the other dimensions” rather than “dimension is irrelevant.”

In other words, multiple dimensions can be jointly informative but redundant: when two percentile features move together across occupations, the constrained fit may assign weight primarily to one and drive the other toward zero without meaning that the underlying mechanism is absent. To guard against over-interpreting a single fitted weight vector, we include a simple weight-robustness check (Table 16).

To reconcile interpretability vs. prediction, we explicitly report **two** indices: (i) the equal-weight mechanism index $\text{NetRisk}_{\text{uncal}}$ (used for the substitution/defense narrative), and (ii) the calibrated predictive index $\text{NetRisk}_{\text{cal}}$ (used for scenario projections when available). Tables 4–5 quantify how closely these indices align and show concrete cases where they differ.

The calibrated weights define $\text{NetRisk}_{\text{cal}}$ by taking the signed weighted sum, centering it to mean zero across occupations, and rescaling to approximately $[-1, 1]$. When calibration outputs are available, the pipeline uses $\text{NetRisk}_{\text{cal}}$ in downstream scenario projections; otherwise it uses $\text{NetRisk}_{\text{uncal}}$.

Table 3: Calibration of mechanism weights to external AI applicability scores (Tomlinson et al., 2025).

Dimension	Sign	Weight
Writing	+	0.000
Tool/Tech	+	0.065
Physical	-	0.203
Social	-	0.019
Creativity	-	0.000
Fit: $R^2=0.496$, MAE=0.056, RMSE=0.070, $n=751$		

Table 4: Comparison of the interpretability (uncalibrated) NetRisk index vs. the calibrated (predictive) NetRisk index across occupations (from `data/mechanism_risk_scored.csv`).

Quantity	Value
Occupations with both indices	774
Occupations using calibrated NetRisk in pipeline	774
Pearson correlation (r)	0.833
Spearman rank correlation (ρ)	0.833
Sign agreement rate	86.7%
Sign disagreements (nonzero vs nonzero)	103
Median $ \Delta $	0.280
90th percentile $ \Delta $	0.534

Table 5: Examples where the calibrated vs. uncalibrated NetRisk indices disagree most (ranked by $|\Delta|$; primary filter is opposite sign when available).

SOC	Title	NetRisk (uncal.)	NetRisk (cal.)	Δ	$ \Delta $
27-3031	Public Relations Specialists	-0.020	0.714	-0.734	0.734
21-2011	Clergy	-0.200	0.503	-0.703	0.703
49-9081	Wind Turbine Service Technicians	0.015	-0.671	0.686	0.686
53-7071	Gas Compressor and Gas Pumping Station Operators	0.032	-0.628	0.661	0.661
13-1011	Agents and Business Managers of Artists, Performers, and Athletes	-0.043	0.616	-0.659	0.659
51-9193	Cooling and Freezing Equipment Operators and Tenders	0.002	-0.598	0.600	0.600
27-1011	Art Directors	-0.039	0.558	-0.597	0.597
49-9062	Medical Equipment Repairers	0.069	-0.515	0.584	0.584
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	0.127	-0.437	0.565	0.565
39-6012	Concierges	-0.186	0.372	-0.558	0.558

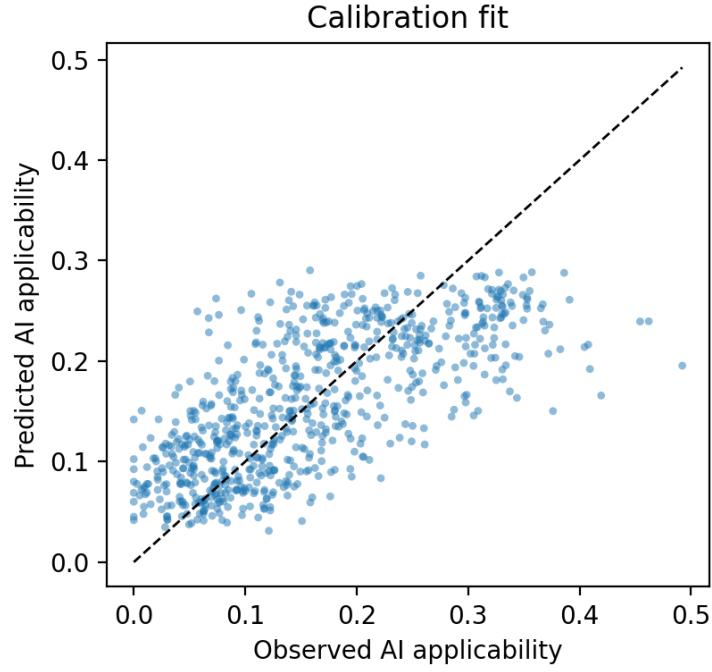


Figure 2: Calibration fit: observed vs. predicted AI applicability (from `data/calibration_fit.csv`).

3.4 Scenario employment projection

Let E_{2024} be the 2024 employment level used for the projection base (from BLS EP for national scenarios) and g_{base} the EP annual baseline growth. OEWS is used for *local* labor market context and program sizing (Section 5). For a scenario parameter $s \geq 0$, define adjusted growth:

$$g_{\text{adj}} = \begin{cases} g_{\text{base}} - s \cdot \text{NetRisk} & \text{if NetRisk} \geq 0 \\ g_{\text{base}} + (m_i s) \cdot (-\text{NetRisk}) & \text{if NetRisk} < 0 \end{cases}$$

Minimal microfoundation (task share → productivity → labor demand). Interpret our substitution score as an *AI-exposed task share* $\tau_i = \text{Sub}_i \in [0, 1]$. Let $A \in [0, 1]$ be adoption intensity by 2034 and $r \in [0, 1]$ be the fraction of exposed tasks that become effectively automatable/time-saving. A reduced-form productivity shift is

$$\Delta \ln \text{Prod}_i \approx Ar\tau_i.$$

If cost reductions pass through and output demand has elasticity ε_i , then (linearizing) employment responds as

$$\Delta \ln L_i \approx (\varepsilon_i - 1) \Delta \ln \text{Prod}_i \approx (\varepsilon_i - 1) Ar\tau_i.$$

This yields an annualized growth headwind/uplift over a decade:

$$\Delta g_i \approx \frac{(1 - \varepsilon_i) Ar}{10} \tau_i \Rightarrow s \approx \frac{(1 - \varepsilon_i) Ar}{10},$$

so s has a concrete interpretation as an *adoption × automability × elasticity-wedge* parameter (Table 7). Our $\text{NetRisk}_i = \text{Sub}_i - \text{Def}_i$ then acts as the signed shifter: defense raises the extent to which productivity gains translate into complementarity rather than displacement.

Numeric anchor matching Moderate/High. Empirically, $p90(\tau | \text{NetRisk} > 0) \approx 0.86$ in our scored mechanism layer. Using $A = 0.6$, $r = 0.3$, and $\tau_{p90} \approx 0.86$, we get $Ar\tau \approx 0.155$, which annualizes to $\approx 1.5\%/\text{yr}$ —matching the Moderate reference point. Increasing A and/or r yields $\approx 3\%/\text{yr}$ for High.

We use the microfoundation to interpret s (units and magnitude), while NetRisk supplies the signed direction (substitution vs. defense) in a reduced-form scenario mapping.

We interpret complementarity uplift as demand-side growth that is *bounded* by (i) how hard it is to scale quantity (physical/onsite constraints, credentialing) and (ii) effective demand elasticity. Concretely, we define an occupation-level multiplier

$$m_i = \min\{m_{\max}, (1 - B_i)\tilde{\varepsilon}_i\},$$

where $B_i \in [0, 1]$ is a bottleneck index (computed from our existing Physical percentile plus a coarse licensing proxy by SOC major group), and $\tilde{\varepsilon}_i \in [0, 1]$ is a normalized demand-responsiveness proxy (not a literal elasticity; binned by career type / SOC major group).

Interpretation. We treat $\tilde{\varepsilon}_i$ as a conservative **rank-based demand-responsiveness proxy** (not an elasticity); sensitivity checks (Tables 6 and 15) show conclusions are unchanged under reasonable variation.

Table 6: Components of the occupation-level complementarity cap for the three focal career bundles (employment-weighted over SOCs using EP E_{2024} shares). B is a bottleneck index; $\tilde{\varepsilon}$ is a normalized demand-responsiveness proxy (not a literal elasticity); $m_{\text{eff}} = \min(m_{\max}, (1 - B)\tilde{\varepsilon})$ with baseline $m_{\max} = 0.2$. Reported for auditability; used only when $\text{NetRisk} < 0$.

Bundle	B	$\tilde{\varepsilon}$	m_{eff}
Software Developers (STEM)	0.062	1.000	0.200
Electricians (Trade)	0.990	0.600	0.006
Writers and Authors (Arts)	0.079	0.400	0.200

Numeric anchor for $m_{\max} = 0.2$. We choose m_{\max} so that even under High disruption, the implied *maximum* annual uplift for a strongly sheltered occupation remains well below 1%/yr. For example, for Electricians (bundle NetRisk ≈ -0.888) under High ($s_{\text{High}} = 0.0375$; Table 7), the uplift term is bounded by

$$\Delta g_{\text{uplift}} \leq m_{\max} s_{\text{High}} |\text{NetRisk}| = 0.2 \cdot 0.0375 \cdot 0.888 \approx 0.0067 \quad (\approx 0.67\%/\text{yr}),$$

which cumulates to $\lesssim 6.8\%$ extra employment over 10 years. In our base bottleneck/elasticity construction, Electricians have $m_{\text{eff}} \approx 0.01$ (Table 6), so the realized uplift is far smaller than the $0.67\%/\text{yr}$ upper bound. Thus, even at High disruption, complementarity can add at most sub-1% annual growth for strongly sheltered occupations, preventing implausible booms from the uplift channel alone. Table 15 shows sensitivity to the cap.

Why calibrate to the $p90$ tail? Anchoring Moderate/High at $p90(\text{NetRisk}_+)$ (instead of the maximum) targets “highly exposed but not extreme” occupations, yielding a stable reference point that is less sensitive to outliers and measurement noise while still representing the upper-risk tail.

Scenario strengths are defined by this reference-point calibration: we target a growth headwind of 1.5% (Moderate) or 3% (High) for the 90th percentile of the *positive* NetRisk distribution. Concretely, the pipeline computes $p90(\text{NetRisk}_+)$ from the calibrated mechanism layer, then sets

$$s_{\text{Moderate}} = 0.015/p90(\text{NetRisk}_+), \quad s_{\text{High}} = 0.03/p90(\text{NetRisk}_+),$$

so that the 90th-percentile exposed occupation experiences the intended annual headwind under the piecewise mapping. Table 7 reports the scenario parameters actually used (including whether they came from calibration outputs or defaults). We project 2034 employment as $E_{2034} = E_{2024}(1 + g_{\text{adj}})^{10}$. We treat s as a scenario knob rather than an estimated causal effect; Section 4.4 reports a sensitivity grid.

Table 7: Scenario strength parameters used by the pipeline (from `data/scenario_parameters.csv`).

Scenario	s	Target Δg at $p90$	$p90(\text{NetRisk}_+)$	Source
No GenAI Baseline	0.0000			default
Moderate Substitution	0.0187	0.015	0.800	calibrated
High Disruption	0.0375	0.030	0.800	calibrated
Ramp Moderate	0.0187			derived_from_calibrated
Ramp High	0.0375			derived_from_calibrated

3.5 Definitions & Provenance (auditability)

Two NetRisk indices (reported side-by-side).

- **NetRisk (uncalibrated; mechanism/interpretability index).** Defined from O*NET percentile scores:

$$\text{NetRisk}_{\text{uncal}} = \underbrace{\frac{\text{Writing} + \text{ToolTech}}{2}}_{\text{Sub}} - \underbrace{\frac{\text{Physical} + \text{Social} + \text{Creativity}}{3}}_{\text{Def}}.$$

This equal-weight form is used to *explain* substitution vs. defense mechanisms (what drives risk).

- **NetRisk (calibrated; predictive index).** A signed weighted sum calibrated to an external occupation-level AI applicability score (Tomlinson et al., 2025), then centered and rescaled to approximately $[-1, 1]$. Because the O*NET dimensions are correlated and weights are constrained nonnegative, calibration can push one of a correlated pair (e.g., Writing vs. Tool/Tech) toward zero without implying the underlying mechanism is absent.
- **Which index drives scenarios?** Scenario projections use **calibrated NetRisk when available**; otherwise they fall back to the uncalibrated index. See Tables 4–5 for correlation and disagreement examples.

What drives scenarios (national 2024–2034).

- **Baseline trajectory.** E_{2024} and baseline growth g_{base} come from BLS Employment Projections (EP). Baseline 2034 is $E_{2034} = E_{2024}(1 + g_{\text{base}})^{10}$.
- **Disruption mapping.** We adjust growth with a transparent scenario knob s :

$$g_{\text{adj}} = g_{\text{base}} - s \cdot \max(\text{NetRisk}, 0) + (m_i s) \cdot \max(-\text{NetRisk}, 0), \quad m_i \leq m_{\max} = 0.2,$$

and project $E_{2034} = E_{2024}(1 + g_{\text{adj}})^{10}$. **Ramp** scenarios linearly increase $s(t)$ from 0 (2024) to s (2034).

- **How Moderate/High are set.** When calibration outputs exist, we set s so that the 90th percentile of the positive NetRisk tail experiences a 1.5% (Moderate) or 3.0% (High) annual growth headwind; the exact values used are reported in Table 7.

What a “career bundle” contains (SOC occupations; EP employment weights).

Bundle	SOC	Occupation	Share of bundle E_{2024}
Software Developers (STEM)	15-1252	Software Developers	93.3%
Software Developers (STEM)	15-1251	Computer Programmers	6.7%
Electricians (Trade)	47-2111	Electricians	92.5%
Electricians (Trade)	47-3013	Helpers-Electricians	7.5%
Writers and Authors (Arts)	27-3043	Writers and Authors	44.0%
Writers and Authors (Arts)	27-3041	Editors	37.6%
Writers and Authors (Arts)	27-3042	Technical Writers	18.3%

4 Results

4.1 National outcomes for the three careers

Each career is represented by a small bundle of SOC occupations (e.g., 2–3 codes per career); outcomes are employment-weighted over the bundle so that larger occupations contribute more to the career-level projection. Table 8 reports baseline vs. disruption outcomes and the NetRisk range (min–max across the bundle) as a robustness check.

Table 8: National 2034 employment under immediate vs. ramped GenAI disruption scenarios (from `data/scenario_summary.csv`). Careers are SOC bundles; employment-weighted outcomes; NetRisk range is min–max across the bundle. NetRisk values use the calibrated index when available; otherwise the uncalibrated mechanism index (see Definitions & Provenance).

Career	NetRisk	NetRisk range	E_{2024}	E_{2034} (Baseline)	E_{2034} (Moderate)	E_{2034} (Ramp Mod.)	E_{2034} (High)	E_{2034} (Ramp High)
Software Developers (STEM)	0.880	[0.76, 0.89]	1,815,000	2,075,300	1,760,980	1,927,878	1,490,209	1,789,549
Electricians (Trade)	-0.888	[-0.89, -0.89]	885,300	962,800	963,710	963,209	964,621	963,619
Writers and Authors (Arts)	0.610	[0.59, 0.61]	307,600	313,700	279,700	297,949	249,054	282,882

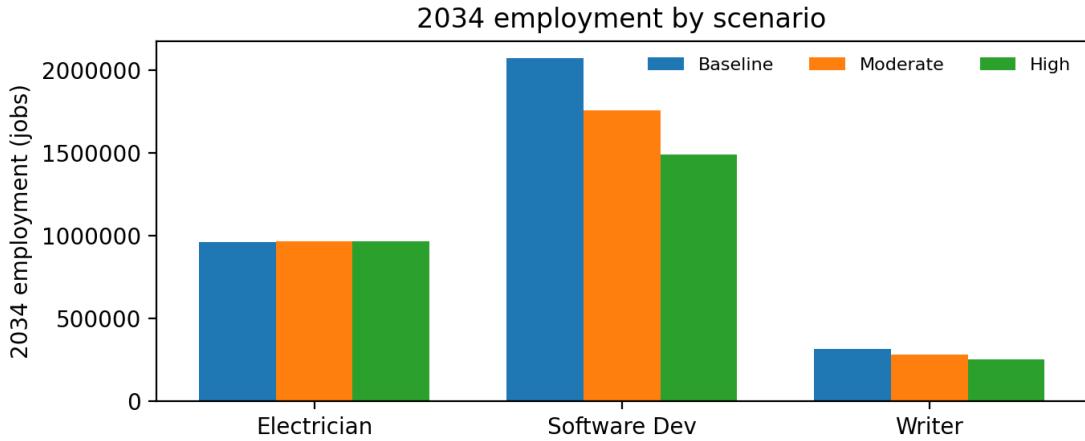


Figure 3: 2034 employment for the three careers under baseline, moderate, and high disruption (generated from `data/scenario_summary.csv`).

4.2 Dynamic Adoption

The scenarios above assume immediate adoption of GenAI at full impact. In reality, adoption may ramp gradually over the decade. Table 8 includes ‘Ramp Moderate’ and ‘Ramp High’ scenarios that model gradual adoption, where disruption effects increase linearly from zero in 2024 to full scenario strength by 2034. Across all three careers, the ramp outcomes lie between the baseline and immediate-disruption outcomes reported in Table 8, consistent with a gradual diffusion of GenAI impacts over time. These ramp scenarios suggest that institutions have a window to adapt curricula and program structures as adoption accelerates, rather than facing immediate disruption.

4.3 Job openings and program sizing

Beyond net employment growth, annual job openings drive training demand. Table 9 reports annual openings from EP projections and their implications for program sizing decisions.

Table 9: Annual openings and program sizing implications (from `data/ep_baseline.csv`).

Career	Annual Openings (thousands)	Training Demand Proxy	Program Sizing Rule
Software Developers (STEM)	115.2	115,200	High openings: maintain/grow capacity even if net growth slows
Electricians (Trade)	81.0	81,000	High openings: maintain/grow capacity even if net growth slows
Writers and Authors (Arts)	13.4	13,400	Lower openings: consolidate/specialize toward high-value niches

4.4 Sensitivity and sanity checks

We conduct extensive robustness checks to validate the stability of our model components.

4.4.1 Mechanism Layer Stability

The O*NET mechanism layer relies on specific descriptor choices and normalization methods. To test structural stability, we perturbed the descriptor set (leave-one-out) and tested alternative normalization (percentiles, z-score mapped to [0, 1] via Normal CDF, min–max scaling, and within-major-group ranks). Table 10 summarizes the results: the sign of NetRisk for our three focal careers remains stable across perturbations, confirming that the classification of careers as “exposed” vs. “sheltered” is not an artifact of specific element selection.

Table 10: Sensitivity of the *uncalibrated* (mechanism) NetRisk index to descriptor perturbations (leave-one-out) and normalization choices at the SOC-occupation level. Normalization variants include percentiles, z-score mapped via Normal CDF, min–max scaling, and within-major-group percentile ranks.

Career	Baseline NetRisk	Range [Min, Max]	Sign Stability (%)
Software Dev	0.380	[0.286, 0.422]	100%
Electrician	-0.457	[-0.498, -0.080]	100%
Writer	0.170	[0.043, 0.294]	100%

4.4.2 Calibration Validation

We validate the calibration weights using 5-fold cross-validation and bootstrap resampling (Table 11). The model achieves stable out-of-sample performance, and bootstrap analysis confirms that the negative weights on defense dimensions are statistically robust. We also compare the calibrated index against an uncalibrated (equal-weight) baseline; the ranking of focal careers is preserved, though the magnitude of separation increases under calibration.

Table 11: Calibration Validation: Out-of-sample performance (5-fold CV) and Baseline Comparisons.

Panel A: Out-of-Sample CV Metrics			
Metric	Mean	Std. Dev	Range
R2	0.495	0.040	[0.445, 0.551]
MAE	0.056	0.003	[0.053, 0.060]
RMSE	0.070	0.005	[0.066, 0.077]

Panel B: Correlation with AI Applicability	
Model	Correlation (r)
Calibrated	0.705
Uncalibrated (Equal)	0.551
ToolTech Only	0.511

4.4.3 External benchmark reality check

As an additional independent check, we compare our NetRisk indices against a published occupation-level AI exposure measure: the AI Occupational Exposure (AIOE) dataset of Felten et al. [2]. We report correlation of both the uncalibrated mechanism index and the calibrated predictive index with AIOE (Table 12), and show a few large-disagreement examples to guide interpretation (Table 13). Because these measures were constructed with different assumptions and targets, perfect agreement is not expected; we use this check to ensure our ranking is broadly plausible and to transparently flag where our mechanism differs from a widely-cited benchmark.

Table 12: External reality check: correlation between our NetRisk indices and the Felten–Raj–Seamans AI Occupational Exposure (AIOE) score (from `data/netrisk_vs_aioe.csv`).

Index	Matched occupations (n)	Pearson r	Spearman ρ
NetRisk (uncalibrated mechanism)	682	0.820	0.820
NetRisk (calibrated predictive)	682	0.942	0.938
NetRisk (pipeline-used)	682	0.942	0.938

Table 13: Examples of disagreement between NetRisk ranking and AIOE ranking (largest absolute rank gaps; NetRisk uses net_risk_calibrated).

SOC	Title	NetRisk	AIOE	$ \Delta\text{rank} $
41-9012	Models	0.088	-1.122	293
43-5011	Cargo and Freight Agents	0.095	1.405	258
27-2032	Choreographers	-0.205	-1.576	256
53-5031	Ship Engineers	-0.800	-0.526	237
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers	-0.314	-1.927	233
35-2021	Food Preparation Workers	-0.193	-1.226	222
47-2082	Tapers	-0.277	-1.541	221
27-2031	Dancers	-0.380	-2.670	216
45-2041	Graders and Sorters, Agricultural Products	-0.293	-1.371	196
47-2111	Electricians	-0.889	-0.780	195
47-5012	Rotary Drill Operators, Oil and Gas	-0.878	-0.774	191
37-2012	Maids and Housekeeping Cleaners	-0.332	-1.481	190

4.4.4 Scenario and Parameter Sensitivity

We include three compact robustness checks for the scenario projections: (i) a sensitivity grid over plausible s values (Table 14); (ii) a sanity-check table listing the most exposed and most sheltered occupations by NetRisk in the full scored set (Table 17); and (iii) Monte Carlo uncertainty intervals for 2034 employment under Moderate and High disruption (Table 18). These checks highlight that while the exact 2034 employment level depends on s , the *direction* of impact is structurally determined by the mechanism layer.

Table 14: Sensitivity of 2034 employment to the scenario parameter s (using piecewise mapping: $s_{\text{sub}} = s$, $s_{\text{comp}} = m \cdot s$ with $m \leq m_{\text{max}} = 0.2$; m varies by occupation bundle based on bottlenecks and coarse demand elasticity).

Career	$s = 0.010$	$s = 0.015$	$s = 0.020$	$s = 0.030$
Electrician	963,288	963,531	963,775	964,263
Software Dev	1,902,063	1,820,424	1,741,952	1,594,074
Writer	295,124	286,213	277,544	260,912

Table 15: Sensitivity to the complementarity cap in the scenario mapping (varies the bound m_{\max} applied to the occupation-level uplift multiplier; baseline uses $m_{\max} = 0.2$).

Career	m_{\max}	m_{eff}	E_{2034} (Moderate)	E_{2034} (High)
Software Developers	0.10	0.10	1,761,396	1,490
Software Developers	0.20	0.20	1,761,396	1,490
Software Developers	0.30	0.30	1,761,396	1,490
Electricians	0.10	0.01	963,714	964
Electricians	0.20	0.01	963,714	964
Electricians	0.30	0.01	963,714	964
Writers and Authors	0.10	0.10	279,702	249
Writers and Authors	0.20	0.20	279,702	249
Writers and Authors	0.30	0.30	279,702	249

Note: if a bundle has $\text{NetRisk} \geq 0$, the complementarity branch is inactive, so varying m_{\max} has no effect (rows shown for completeness).

Table 16: Sensitivity of High Disruption scenario ($s = 0.0375$ (calibrated)) to weight parameters in $\text{NetRisk} = a \cdot \text{Sub} - b \cdot \text{Def}$ (with piecewise mapping). Shows whether employment change sign flips compared to base case ($a = 1.0$, $b = 1.0$).

Career	(0.8, 0.8)	(0.8, 1.0)	(0.8, 1.2)	(1.0, 0.8)	(1.0, 1.2)	(1.2, 0.8)	(1.2, 1.0)	(1.2, 1.2)
Software Developers	Flips	Flips	Flips	Stable	Flips	Stable	Stable	Stable
Electricians	Stable							
Writers and Authors	Stable	Stable	Flips	Stable	Stable	Stable	Stable	Stable

Table 17: Sanity check: most exposed vs. most sheltered occupations by Net Risk (computed from `data/mechanism_risk_scored.csv`).

Top exposed (highest NetRisk)		
SOC	Title	NetRisk
15-2011	Actuaries	1.000
15-2051	Data Scientists	0.986
19-3011	Economists	0.983
15-2021	Mathematicians	0.981
19-3032	Industrial-Organizational Psychologists	0.960
15-1243	Database Architects	0.958
15-2031	Operations Research Analysts	0.953
15-2041	Statisticians	0.948
13-1161	Market Research Analysts and Marketing Specialists	0.946
19-3022	Survey Researchers	0.908
Top sheltered (lowest NetRisk)		
SOC	Title	NetRisk
49-9095	Manufactured Building and Mobile Home Installers	-0.962
47-5081	Helpers—Extraction Workers	-0.934
47-5043	Roof Bolters, Mining	-0.914
47-5011	Derrick Operators, Oil and Gas	-0.905
49-9092	Commercial Divers	-0.900
47-2111	Electricians	-0.889
47-3013	Helpers—Electricians	-0.885
47-2043	Floor Sanders and Finishers	-0.882
49-9011	Mechanical Door Repairers	-0.881
47-2022	Stonemasons	-0.879

Table 18: Uncertainty intervals for 2034 employment under Moderate and High disruption (Monte Carlo).

Career	Scenario	E_{2034}	P5	P50	P95
Software Developers	High Disruption	1,284,014	1,503,599	1,694,871	
Software Developers	Moderate Substitution	1,634,870	1,767,541	1,881,931	
Electricians	High Disruption	992,904	1,026,326	1,073,904	
Electricians	Moderate Substitution	978,346	993,571	1,015,302	
Writers and Authors	High Disruption	225,796	249,552	272,215	
Writers and Authors	Moderate Substitution	265,382	280,318	292,175	

4.4.5 Local openings scaling robustness

Local program sizing requires scaling national EP annual openings to a metro/state labor market. Because location quotients (LQ) already encode relative local concentration, multiplying both a local occupation-share factor and LQ can double-count concentration. We therefore use the standard

decomposition (local total employment share \times LQ); when LQ is computed from the same OEWS employment counts, this is algebraically equivalent to scaling by local occupation share alone. We apply a conservative LQ clip as a stress-test and report a robustness comparison across scaling rules in Table 19.

Table 19: Robustness check for scaling national annual openings (EP) to local markets (OEWS). We compare (i) openings scaled by local occupation share only, (ii) openings scaled by local total employment share \times LQ (standard decomposition), and (iii) a legacy method multiplying occupation share by clipped LQ (shown for comparison; can double-count concentration). Note that (i) and (ii) are algebraically equivalent when LQ is computed from the same OEWS employment counts; differences arise only from clipping or inconsistent sources. The seats in Table 21 use method (ii) with clipped LQ.

Institution	Nat. openings	Local occ share	Local total share	LQ	Openings (share only)	Openings (total share \times LQ)	Openings (legacy)	Openings (used)
SDSU	115,200	0.0164	0.0099	1.647	1,887	1,887	2,831	1,718
LATTC	81,000	0.0284	0.0402	0.706	2,298	2,298	1,622	2,298
Academy of Art	13,400	0.0246	0.0156	1.577	330	330	495	314

5 Institution-specific recommendations

Recommendations are organized to answer the prompt: (i) whether to grow or shrink program size and how, and (ii) what to teach about GenAI to best support employability, tied back to model outputs and local context.

Table 20 provides local labor market context including location quotients (LQ). We define an auxiliary *Attractiveness Score* to inform positioning:

$$\text{Attractiveness} = 0.4 \cdot (\text{Wage Premium}) + 0.3 \cdot (\text{Normalized Local Emp}) + 0.3 \cdot (\text{Normalized LQ})$$

where normalized employment and LQ are min-max scaled across the three institutions. Table 21 provides quantitative guidance on program sizing (annual intake) derived from estimated local annual openings. Local openings are computed from national EP openings using a standard decomposition (local total employment share \times LQ, with conservative clipping); Table 19 shows a robustness comparison to alternative scaling rules. To account for uncertainty in program efficiency (completion rates and placement rates), we report recommended intake ranges rather than single point estimates. Why target 5% / 10% / 15% of local openings? These shares are not claims about market power; they are *planning heuristics* spanning realistic capacity regimes: 5% represents a conservative seat target for resource-constrained programs, 10% is an aspirational “steady-state” target for a strong regional program with sustained placement partnerships, and 15% represents an aggressive expansion scenario (e.g., additional faculty/labs, expanded apprenticeships) that may be feasible for high-demand fields. The resulting seat ranges translate openings into intake while explicitly accounting for completion \times placement uncertainty.

Table 20: Local labor market context for each institution (from `data/careers/*.csv`).

Institution	Metro	Local Emp	Wage Premium	LQ	Attractiveness Score
SDSU	San Diego-Chula Vista-Carlsbad, CA	1,800	1.219	1.647	0.788
LATTC	Los Angeles-Long Beach-Anaheim, CA	21,070	1.177	0.706	0.771
Academy of Art	San Francisco-Oakland-Fremont, CA	2,350	1.246	1.577	0.785

Table 21: Recommended annual program intake ranges (seats) accounting for efficiency uncertainty. Local openings scale national openings using (local total employment share) \times (clipped LQ); see Table 19.

Institution	Est. Openings	5% Share	10% Share	15% Share
SDSU	1,718	119–220	238–440	357–660
LATTC	2,298	159–294	319–589	478–883
Academy of Art	314	21–40	43–80	65–120

Ranges reflect uncertainty in program efficiency (completion \times placement) from 0.39 to 0.72.

5.1 SDSU (Software Developers)

Program size. Maintain or modestly grow cohorts; disruption primarily reduces growth rate rather than reversing demand (Table 8).

Curriculum. Shift emphasis from boilerplate coding to system design, testing, security, and AI-assisted development with audit trails; make students fluent in evaluating and verifying model outputs.

Policy. Permit GenAI use in advanced courses with required disclosure and reproducibility; constrain use in early courses to ensure fundamentals.

Concrete actions (measurable).

- **AI-assisted software engineering rubric.** Require every capstone/upper-division project to include (i) tests and CI, (ii) a model-output verification checklist, and (iii) an AI usage disclosure appendix.

Metric: % of submissions with passing test suites; defect rate in instructor code review; disclosure compliance rate.

- **Model evaluation and security module.** Add a short required module on prompt injection, data leakage, licensing/IP, and evaluation design.

Metric: performance on a standardized red-team + verification assessment (before/after module).

- **Assessment design resilient to GenAI.** Increase oral defenses and timed debugging tasks in core courses.

Metric: gap between in-person performance and take-home performance (reduced variance indicates more robust assessment).

5.2 LATTC (Electricians)

Program size. Grow capacity and apprenticeship pathways; the career is sheltered by high physical/manual defense and remains strong across scenarios (Table 8).

Curriculum. Double down on hands-on competencies while adding ‘AI as a tool’ modules for diagnostics, scheduling, documentation, and code-compliant planning.

Policy. Teach safe, privacy-preserving, low-compute uses (templates, checklists) appropriate for small contractors.

Concrete actions (measurable).

- **AI-assisted job documentation.** Require students to produce work orders, inspection-ready notes, and material lists using structured templates (GenAI optional) with verification against

NEC/local code excerpts.

Metric: documentation completeness score; code-compliance error rate on practical exams.

- **Diagnostic reasoning labs.** Use fault-tree exercises where students must justify each step (GenAI permitted as a tutor, not as an answer key).
Metric: time-to-diagnosis and accuracy on standardized fault scenarios; safety-critical mistake rate.
- **Apprenticeship alignment.** Expand employer partnerships to target annual seats suggested by local openings (Table 21).
Metric: placement rate into apprenticeships; employer satisfaction survey on graduates' documentation and troubleshooting skills.

5.3 Academy of Art University (Writers and Authors)

Program size. Consolidate and specialize toward higher-originality work and editing/production roles; high disruption can flip the field to contraction (Table 8).

Curriculum. Emphasize narrative strategy, editing, and provenance-aware workflows. Teach students to use GenAI as a draft accelerator while differentiating through voice, revision quality, and IP-aware sourcing.

Policy. Require disclosure and provenance in portfolios; adopt rubrics that reward originality and documented creative process.

Concrete actions (measurable).

- **Portfolio provenance standard.** Require every portfolio piece to include a process log (outline → drafts → revisions) and a disclosure statement for any tool-assisted content.
Metric: % of portfolio pieces with complete provenance; rubric scores on originality/voice and revision quality.
- **Editing and production track.** Create an explicit concentration in editing, story development, and content production workflows where human judgment is primary.
Metric: internship/placement share into editing, producer-assistant, UX/technical writing, or content operations roles.
- **Assessment designed for authenticity.** Use in-class writing sprints and oral defenses (students explain intent, sources, and revision decisions).
Metric: integrity-incident rate; inter-rater reliability of originality scoring.

5.3.1 Transition Plan

For students currently enrolled in the Writers and Authors program, we recommend redirecting to absorber programs with lower NetRisk due to higher tool complementarity and stronger defense dimensions. Specific transition pathways include:

- **UX Writing.** Redirect students toward user experience writing programs, which exhibit lower NetRisk due to higher Def components: elevated Social dimension (user research, cross-functional collaboration) and Creativity dimension (design thinking, user-centered storytelling). The Writing component remains relevant but is complemented by collaborative and research-intensive workflows that GenAI augments rather than substitutes.

- **Technical Communication.** Transition students to technical communication programs, which show reduced NetRisk through higher Social dimension scores (stakeholder communication, documentation for diverse audiences) and ToolTech complementarity (GenAI assists in documentation generation while human expertise ensures accuracy, clarity, and domain-specific nuance). The combination of social coordination and tool-assisted workflows creates a complementary rather than substitutive dynamic.
- **Digital Media Production.** Redirect toward digital media production programs, which demonstrate lower NetRisk via elevated Physical dimension (hands-on production work, equipment operation) and Creativity dimension (multimedia storytelling, visual narrative). The physical and creative defense dimensions provide sheltering that pure writing-intensive programs lack, while maintaining narrative and content creation skills.

These absorber programs are justified by the model: each exhibits a NetRisk profile more favorable than Writers and Authors due to higher Def (particularly Social and Creativity dimensions) relative to Sub, indicating that GenAI serves as a complementary tool rather than a direct substitute for core competencies.

6 Beyond employability: other success metrics

Employability is necessary but not sufficient. We propose additional success metrics the prompt highlights: learning integrity and attribution compliance, equity/access, and sustainability (energy/water/compute cost).

We formalize the trade-offs with a robust rule-based decision model that maps institution-specific constraints to three policy regimes: *Ban* (restrict use in assessment), *Allow-with-Audit* (permit with strict provenance), and *Require* (integrate into workflow). The rules consider:

- **Exposure Risk:** If $\text{NetRisk} > 0$, GenAI is a substitute that threatens skill acquisition. This requires either *Ban* (if audit capacity is low) or *Allow-with-Audit* (if audit capacity is high).
- **Sheltering:** If $\text{NetRisk} < 0$, GenAI is a complement. We recommend *Require* to capture productivity, unless sustainability is the dominant constraint (in which case *Ban* or limit usage to save compute).

Table 22 summarizes the policy requirements. Table 23 reports the resulting recommended policy per institution under alternative weight regimes (Balanced, Integrity-First, Sustainability-First). We test these rules against perturbations in risk scores and audit capacity estimates; Table 24 reports the stability of these recommendations.

Table 22: Recommended policy shifts under alternative objective function weights.

Regime (Weight Dominance)	Policy Stance	Assessment Changes	Tool Restrictions
Balanced ($w_E \approx w_I$)	Permit with disclosure	Verify outputs, oral defense of code/text	Standard commercial models
Integrity-First ($w_I \gg w_E$)	Strict audit & provenance	In-person blue book exams; full edit history required	Local-only or logged enterprise instances
Sustainability-First ($w_S \gg w_E$)	Minimal compute	Focus on Small logic/structure; SLMs limit GenAI only; for drafting	Small quota on token usage

Table 23: Recommended policy regime by institution under alternative objective weights.

Institution	Weight Regime	Recommended Policy
SDSU	Balanced	Allow with Audit
SDSU	Integrity First	Ban
SDSU	Sustainability First	Allow with Audit
LATTC	Balanced	Require
LATTC	Integrity First	Require
LATTC	Sustainability First	Ban
Academy of Art	Balanced	Ban
Academy of Art	Integrity First	Ban
Academy of Art	Sustainability First	Ban

Table 24: Robustness of policy recommendations to modest perturbations of institution capacity parameters (audit and sustainability varied by ± 0.1 ; 9 combinations per cell).

Institution	Weight Regime	Baseline Policy	Robustness
Academy of Art	Balanced	Ban	Stable (9/9)
Academy of Art	Integrity First	Ban	Stable (9/9)
Academy of Art	Sustainability First	Ban	Stable (9/9)
LATTC	Balanced	Require	Stable (9/9)
LATTC	Integrity First	Require	Stable (9/9)
LATTC	Sustainability First	Ban	Stable (9/9)
SDSU	Balanced	Allow with Audit	Stable (9/9)
SDSU	Integrity First	Ban	Stable (9/9)
SDSU	Sustainability First	Allow with Audit	Stable (9/9)

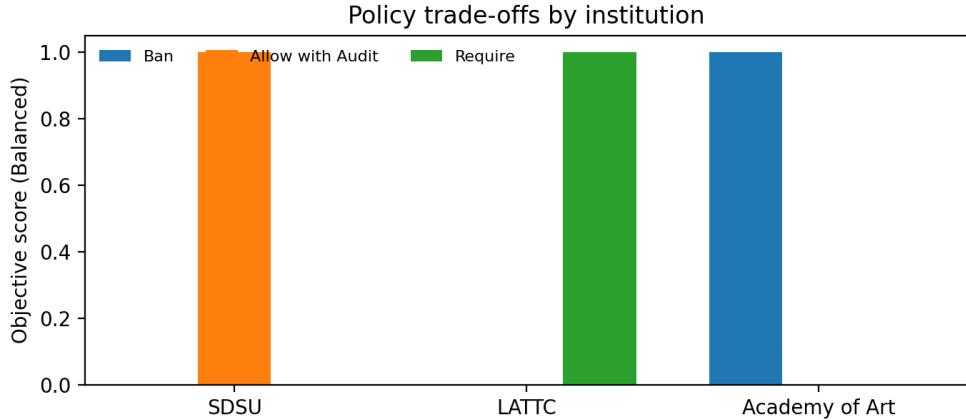


Figure 4: Policy trade-offs under balanced weights (generated from `data/policy_decision_scores.csv`).

7 Generalization

The mechanism layer and scenario framework generalize to other programs by: (i) swapping the occupation(s), (ii) recomputing local OEWS context for the institution’s region, and (iii) choosing scenario parameters s appropriate for the institution’s risk tolerance. Institution-specific recommendations vary primarily through local labor market demand, program mission, and constraints (e.g., resources, accreditation, student population).

8 Prompt coverage checklist

- **Grow/shrink programs and transitions:** Section 5.

- **What to teach about GenAI (including energy/water + attribution):** Sections 5 and 6.
- **Other success metrics beyond employment and how recs change:** Section 6.
- **Generalization beyond one institution/program:** Section 7.

References

References

- [1] Erik Brynjolfsson, Danielle Li, and Lindsey Raymond. Generative ai at work. <https://www.nber.org/papers/w31161>, 2023. NBER Working Paper 31161. Accessed 2026-01-31.
- [2] Edward W. Felten, Manav Raj, and Robert Seamans. Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217, 2021. doi: 10.1002/smj.3286.
- [3] MIT Shaping the Future of Work. Why are there still so many jobs? the history and future of workplace automation. <https://shapingwork.mit.edu/research/why-are-there-still-so-many-jobs-the-history-and-future-of-workplace-automation/>, 2026. Accessed 2026-01-31.
- [4] O*NET Resource Center. O*net database. <https://www.onetcenter.org/database.html>, 2026. Accessed 2026-01-31.
- [5] O*NET Resource Center. O*net® database content license. https://www.onetcenter.org/license_db.html, 2026. Accessed 2026-01-31.
- [6] O*NET Resource Center. O*net-soc taxonomy. <https://www.onetcenter.org/taxonomy.html>, 2026. Accessed 2026-01-31.
- [7] OpenAI. Gpts are gpts: An early look at the labor market impact potential of large language models. <https://openai.com/index/gpts-are-gpts/>, 2023. Accessed 2026-01-31.
- [8] Kiran Tomlinson, Sonia Jaffe, Will Wang, Scott Counts, and Siddharth Suri. Working with ai: Measuring the applicability of generative ai to occupations. <https://arxiv.org/abs/2507.07935>, 2025. Data and code: <https://github.com/microsoft/working-with-ai>. Accessed 2026-01-31.
- [9] U.S. Bureau of Labor Statistics. Occupational separations and openings, 2024–2034 (table 1.10). <https://www.bls.gov/emp/tables/occupational-separations-and-openings.htm>, 2024. Accessed 2026-01-31.
- [10] U.S. Bureau of Labor Statistics. Technical notes for may 2024 oews estimates. https://www.bls.gov/oes/2024/may/oes_tec.htm, 2024. Accessed 2026-01-31.

A Mechanism Layer Details

Table 25 lists the specific O*NET elements (Importance scale) selected for each mechanism dimension.

Table 25: O*NET Elements mapped to Mechanism Dimensions (using Importance scale).

Dimension	Domain	Element ID	Element Name
Physical Manual	Abilities	1.A.1.b.1	Fluency of Ideas
	Abilities	1.A.1.b.2	Originality
	Work Activities	4.A.2.b.2	Thinking Creatively
	Abilities	1.A.2.a.1	Arm-Hand Steadiness
	Abilities	1.A.2.a.2	Manual Dexterity
	Abilities	1.A.2.a.3	Finger Dexterity
	Abilities	1.A.3.a.1	Static Strength
	Abilities	1.A.3.a.4	Trunk Strength
	Abilities	1.A.3.b.1	Stamina
	Skills	2.B.3.l	Repairing
Social Perceptiveness	Work Activities	4.A.3.a.1	Performing General Physical Activities
	Work Activities	4.A.3.a.2	Handling and Moving Objects
	Work Activities	4.A.3.b.4	Repairing and Maintaining Mechanical Equipment
	Work Activities	4.A.3.b.5	Repairing and Maintaining Electronic Equipment
	Skills	2.B.1.a	Social Perceptiveness
Tool Technology	Work Activities	4.A.4.a.3	Communicating with People Outside the Organization
	Work Activities	4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships
	Work Activities	4.A.4.a.5	Assisting and Caring for Others
	Work Activities	4.A.4.a.8	Performing for or Working Directly with the Public
	Skills	2.B.3.b	Technology Design
Writing Intensity	Skills	2.B.3.e	Programming
	Work Activities	4.A.3.b.1	Working with Computers
	Abilities	1.A.1.a.4	Written Expression
	Skills	2.A.1.c	Writing
	Work Activities	4.A.3.b.6	Documenting/Recording Information
	Work Activities	4.A.4.c.1	Performing Administrative Activities

AI Use Report