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 and institutions.** We study a STEM career (Software Developers; San Diego State University), a trade career (Electricians; Los Angeles Trade–Technical College), and an arts career (Writers and Authors; Academy of Art University).

- **Data.** We combine BLS Occupational Employment and Wage Statistics (OEWS) for local labor market context with BLS Employment Projections (EP) for national 2024–2034 baselines, and O*NET 30.1 descriptors to build a mechanism layer explaining substitution vs. complementarity [9, 8, 3, 5, 4].

- **Model.** We define five O*NET-based dimensions, compute percentiles across occupations, and form a *Net Risk* index:

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

  Scenario employment uses baseline EP annual growth g_{base} adjusted by a scenario parameter s using a piecewise mapping:

$$g_{\mathrm{adj}} = g_{\mathrm{base}} - s \cdot \max(\mathrm{NetRisk}, 0) + 0.2s \cdot \max(-\mathrm{NetRisk}, 0).$$

  This effectively creates a substitution penalty for exposed occupations while capping the complementarity uplift for sheltered occupations to 20% of the shock magnitude. See Table 4.

- **Headline findings.** Under high disruption, Software Developers remain growing but with a materially reduced decade growth rate; Electricians are comparatively sheltered; Writers and Authors can flip from slight growth to slight contraction (Table 4).

- **Program-size decisions.** SDSU CS: maintain/slight growth; LATTC Electric: grow aggressively; Academy of Art Writing: consolidate/specialize toward higher-originality niches and editing/production workflows (Section 5).

Contents

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 [2, 6, 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 [9].

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 occupation [8].

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 [3, 5, 4].

Attribution. O*NET® data used under the O*NET Database Content License; see References [4].

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 `mechanism_layer_all.csv`	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 $d \in \{\text{Writing}, \text{ToolTech}, \text{Physical}, \text{Social}, \text{Creativity}\}$ 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:

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

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

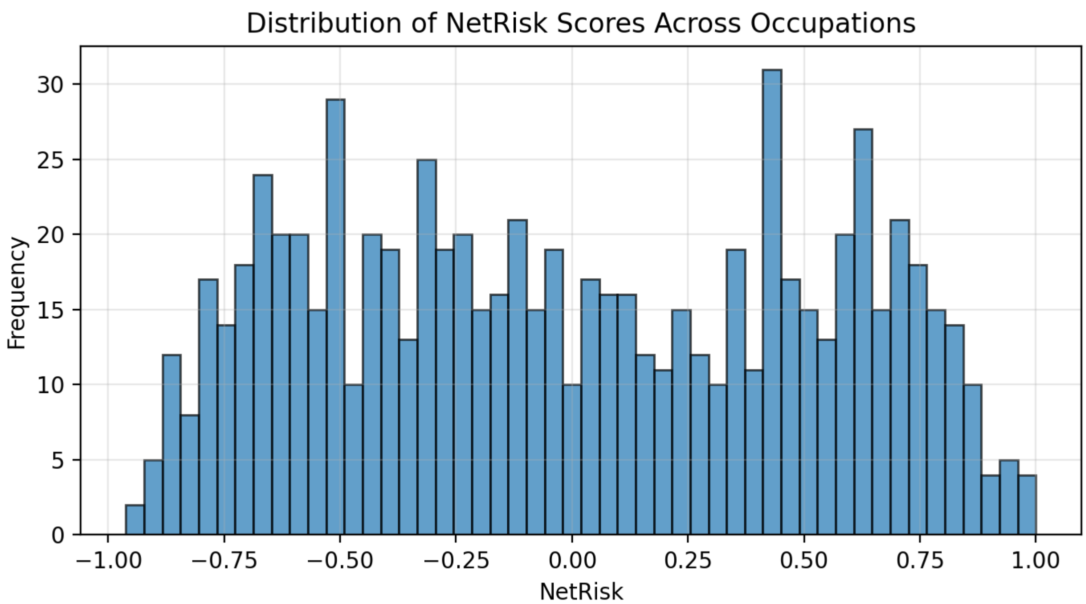

Figure 1: Distribution of NetRisk scores across all occupations in the mechanism layer (from `data/mechanism_risk_scored.csv`).

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 [7]. We fit nonnegative weights on the five dimensions with defense dimensions entering with negative sign. Table 3 reports the calibrated weights and fit metrics; Figure 2 shows observed vs. predicted applicability.

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		

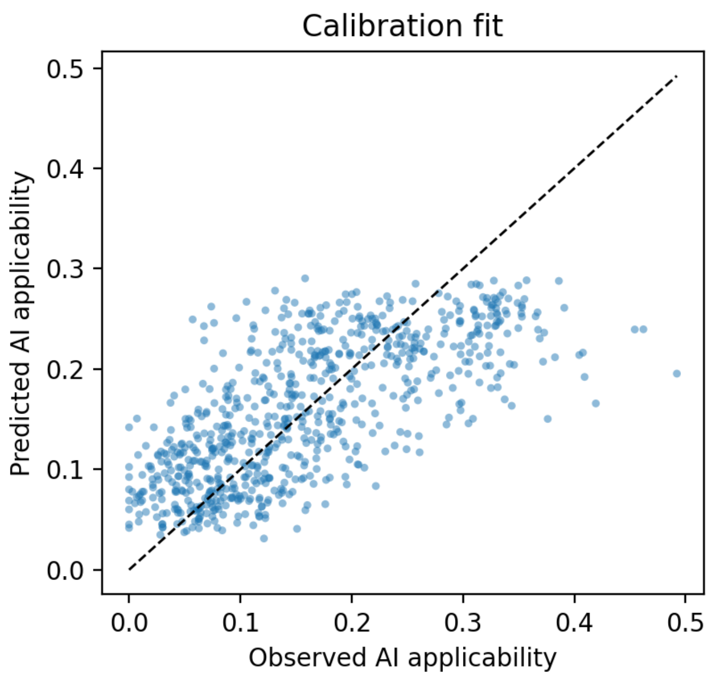

Figure 2: Calibration fit: observed vs. predicted AI applicability (from `data/calibration_fit.csv`).

3.4 Scenario employment projection

Let E_{2024} be the 2024 employment level (from OEWS levels) and g_{base} the EP annual baseline growth. For a scenario parameter $s \geq 0$, define adjusted growth:

$$g_{\text{adj}} = \begin{cases} g_{\text{base}} - s \cdot \text{NetRisk} & \text{if NetRisk} \geq 0 \\ g_{\text{base}} + 0.2s \cdot (-\text{NetRisk}) & \text{if NetRisk} < 0 \end{cases}$$

We use $s \in \{0.015, 0.03\}$ for Moderate and High disruption, then rescale these values using the calibrated NetRisk distribution so that the 90th-percentile exposed occupation experiences a 1.5% or 3% annual growth headwind. The factor 0.2 scales complementarity: while GenAI may help sheltered occupations, we assume the demand boost is smaller than the substitution effect for exposed ones. 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.

4 Results

4.1 National outcomes for the three careers

Table 4 reports baseline vs. disruption outcomes computed from the reproducible pipeline artifacts.

Table 4: National 2034 employment under GenAI disruption scenarios (from `data/scenario_summary.csv`).

Career	NetRisk	E_{2024}	E_{2034} (Baseline)	E_{2034} (High)	Change vs 2024 (High)	High vs Baseline (2034)
Software Developers (STEM)	0.888	1,693,800	1,961,400	1,404,980	-288,820	-556,420
Electricians (Trade)	-0.889	818,700	896,100	957,047	138,347	60,947
Writers and Authors (Arts)	0.615	135,400	140,300	111,224	-24,176	-29,076

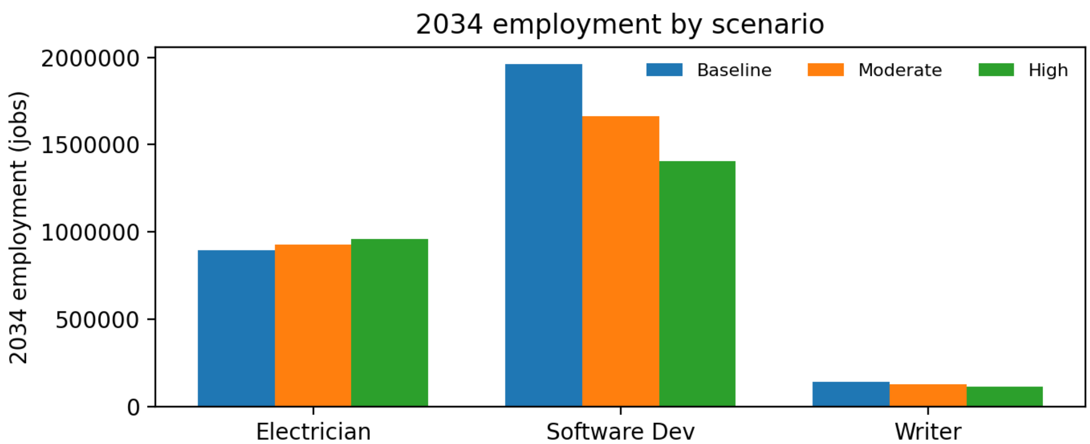

Figure 3: 2034 employment for the three careers under baseline, moderate, and high disruption (generated from `data/scenario_summary.csv`).

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 4 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 4, 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 5 reports annual openings from EP projections and their implications for program sizing decisions.

Table 5: 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 include three compact robustness checks: (i) a sensitivity grid over plausible s values (Table 6); (ii) a sanity-check table listing the most exposed and most sheltered occupations by NetRisk in the full scored set (Table 8); and (iii) Monte Carlo uncertainty intervals for 2034 employment under Moderate and High disruption (Table 9).

Table 6: Sensitivity of 2034 employment to the scenario parameter s (using piecewise mapping: $s_{sub} = s, s_{comp} = 0.2s$).

Career	$s = 0.010$	$s = 0.015$	$s = 0.020$	$s = 0.030$
Electrician	912,007	920,056	928,169	944,587
Software Dev	1,796,313	1,718,554	1,643,838	1,503,112
Writer	131,941	127,932	124,033	116,554

Table 7: Sensitivity of High Disruption scenario ($s = 0.03$) 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	Stable	Stable	Stable	Stable	Stable	Flips	Flips	Stable
Electricians	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Writers and Authors	Stable	Flips	Flips	Stable	Flips	Stable	Stable	Stable

Table 8: 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 9: Uncertainty intervals for 2034 employment under Moderate and High disruption (Monte Carlo).

Career	Scenario	E_{2034} P5	P50	P95
Software Developers	High Disruption	1,208,400	1,417,063	1,599,024
Software Developers	Moderate Substitution	1,541,925	1,668,200	1,777,135
Electricians	High Disruption	924,109	955,204	999,470
Electricians	Moderate Substitution	910,564	924,729	944,948
Writers and Authors	High Disruption	100,772	111,447	121,636
Writers and Authors	Moderate Substitution	118,563	125,280	130,614

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 10 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 11 provides quantitative guidance on program sizing (annual intake) derived from estimated local annual openings.

Table 10: 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	21,080	1.092	1.281	0.897
LATTC	Los Angeles-Long Beach-Anaheim, CA	21,070	1.177	0.706	0.771
Academy of Art	San Francisco-Oakland-Fremont, CA	1,330	1.309	1.783	0.824

Table 11: Recommended annual program intake (seats) based on local openings share.

Institution	Est. Local Openings	Seats (5% share)	Seats (10%)	Seats (15%)
SDSU	1,881	157	313	470
LATTC	1,622	135	270	405
Academy of Art	559	47	93	140

Local openings estimated by scaling national openings by OEWS employment share and LQ: $O_{local} = O_{nat} \cdot (E_{local}/E_{nat}) \cdot \text{LQ}_{clipped}$. Seats are annual cohort intake; assumes 80% completion and 75% placement (net efficiency $\approx$ 0.6).

5.1 SDSU (Software Developers)

Program size. Maintain or modestly grow cohorts; disruption primarily reduces growth rate rather than reversing demand (Table 4).

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.

5.2 LATTC (Electricians)

Program size. Grow capacity and apprenticeship pathways; the occupation is sheltered by high physical/manual defense and remains strong across scenarios (Table 4).

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.

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 4).

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.

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). A simple program objective is:

$$\text{Score} = w_E \cdot \text{Employability} - w_I \cdot \text{IntegrityRisk} - w_S \cdot \text{SustainabilityCost}.$$

When w_I increases, we recommend stricter disclosure/audit requirements and assessment designs robust to code/text generation; when w_S increases, we recommend lower-compute tools and fewer 'always-on" GenAI requirements, especially in resource-constrained settings. Table 12 summarizes how our recommendations shift under these alternative weight regimes.

Table 12: 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 logic/structure; limit GenAI for drafting	Small SLMs only; quota on token usage

We also formalize the trade-offs with a simple multi-objective decision model that scores three policy regimes (Ban, Allow-with-Audit, Require) for each institution under alternative weight regimes. Table 13 reports the recommended policy per institution; Figure 4 visualizes the balanced-case trade-offs.

Table 13: Recommended policy regime by institution under alternative objective weights.

Institution	Weight Regime	Recommended Policy
Academy of Art	Balanced	Ban
Academy of Art	Integrity First	Ban
Academy of Art	Sustainability First	Ban
LATTC	Balanced	Ban
LATTC	Integrity First	Ban
LATTC	Sustainability First	Ban
SDSU	Balanced	Ban
SDSU	Integrity First	Ban
SDSU	Sustainability First	Ban

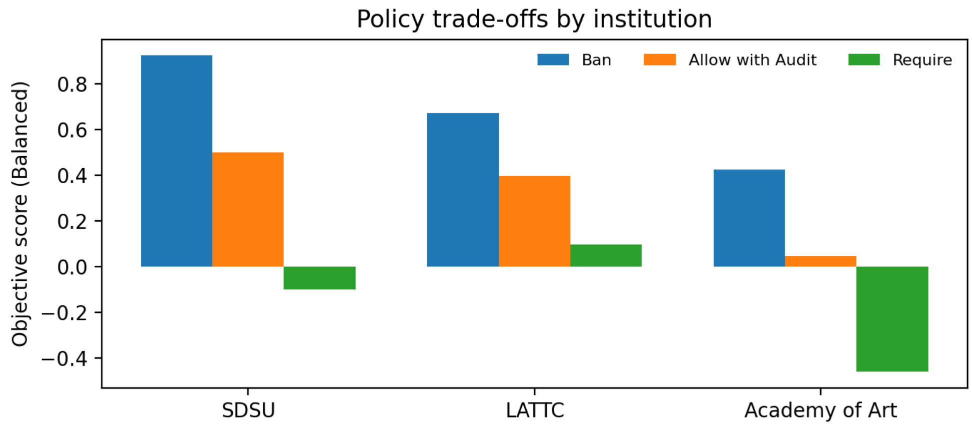

Figure 4: Policy trade-offs under balanced weights (generated from `data/policy_decision_scores.csv`).

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] 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.

[3] O*NET Resource Center. O*net database. https://www.onetcenter.org/database.html, 2026. Accessed 2026-01-31.

[4] O*NET Resource Center. O*net® database content license. https://www.onetcenter.org/license_db.html, 2026. Accessed 2026-01-31.

[5] O*NET Resource Center. O*net-soc taxonomy. https://www.onetcenter.org/taxonomy.html, 2026. Accessed 2026-01-31.

[6] 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.

[7] 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.

[8] 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.

[9] 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 14 lists the specific O*NET elements (Importance scale) selected for each mechanism dimension.

Table 14: O*NET Elements mapped to Mechanism Dimensions (using Importance scale).

Dimension	Domain	Element ID	Element Name
Creativity Originality	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
Physical Manual	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
	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
Social Perceptiveness	Skills	2.B.1.a	Social Perceptiveness
	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
Tool Technology	Skills	2.B.3.b	Technology Design
	Skills	2.B.3.e	Programming
	Work Activities	4.A.3.b.1	Working with Computers
Writing Intensity	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