

To Gen-AI or not to Gen-AI: Sensory-Economic Framework for Aligning Post-secondary Education with an AI-Transformed Labor Market

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Abstract. Generative AI is restructuring labor markets, challenging post-secondary institutions to adapt curricula. This paper develops the GRASP Framework, predicting occupation-specific AI penetration and generating curriculum optimization strategies. Grounded in O*NET data, PULSE forecasts labor demand evolution via a Sensory Resistance Coefficient establishing automation ceilings; CALIBER employs constrained Cobb-Douglas optimization for curriculum transitions. Three career segments are examined: Library Music Producers (Berklee), Gameplay Programmers (USC), and Full-Service Chefs (CIA). Extending beyond employment, COMPASS maps eighteen occupations onto a strategy space of sensory resistance and demand elasticity, classifying careers into Sanctuary, Augmentation, and Pivot zones. The primary innovation disaggregates occupation-level analysis into career segments, revealing within-occupation variation obscured by aggregate assessments.

Keywords: Generative AI, Task Digitalization, Sensory Resistance, Career Segments, Educational Policy.

1. Introduction

1.1. Background

In fewer than five years, Generative AI has evolved from a technical curiosity into an economic force reshaping knowledge production. Unlike earlier automation that displaced routine manual labor, Gen-AI penetrates cognitive and creative domains—writing, coding, composing, designing—once considered uniquely human.

Yet the impact is strikingly uneven. The ILO estimates that 3.3% of the global workforce occupies roles at the highest tier of Gen-AI exposure, rising to 6.2% in high-income economies [1]—but these aggregates mask radical variation. A library music producer faces existential displacement while a chef remains untouched because no model can taste a sauce. Within single professional categories, practitioners face radically different AI exposure.

This heterogeneity presents a critical challenge for post-secondary institutions. How should a music conservatory redesign its curriculum when much of its graduates' output may be AI-generated? Should computer science programs teach students to write code, or to verify AI-written code? Generic prescriptions for “AI literacy” are insufficient. What is needed is a principled framework connecting professional task characteristics to AI disruption magnitude and, from there, to actionable curriculum redesign.

1.2. Problem Restatement

This paper addresses the following questions:

1. Career Analysis: For three careers spanning STEM, Trade, and Arts domains, what are the expected AI disruption trajectories, and what task-level characteristics determine vulnerability?
2. Institutional Recommendations: For a specific institution serving each career, how should curriculum composition, enrollment strategy, and pedagogy evolve?

3. Beyond Employability: What dimensions beyond employment—sustainability, ethics, cognitive autonomy—should inform strategy, and how do recommendations change when these are weighted?
4. Generalization: To what extent can recommendations be extended to the broader occupational landscape?

1.3. Literature Review and Theoretical Foundations

The framework synthesizes four research traditions:

Task Displacement and Productivity Dynamics. The task-based framework [2, 3] establishes that automation reallocates tasks between labor and capital, generating displacement and reinstatement effects. Acemoglu [4] formalizes this macroeconomically; Brynjolfsson et al. [5] document adoption-phase productivity slowdowns; METR [6] confirms short-term friction on complex tasks, justifying verification-cost parameters.

Physical and Cognitive Resistance. Exposure indices [1, 7] map AI capabilities to occupations but mask within-occupation variation. Embodied Cognition theory [8] posits that tasks requiring physical manipulation or sensory feedback resist digital substitution, motivating the Sensory/Physical Resistance Coefficient (S_i).

Human Capital Complementarity. Following Deming [9] and Heckman and Kautz [10], skills are modeled as Cobb-Douglas complements: soft skills account for 25–35% of wage variance, ensuring curriculum retains human-centered training.

Systemic Constraints. Shumailov et al. [11] demonstrate Model Collapse on synthetic data; Luccioni et al. [12] quantify LLM carbon costs, motivating the environmental penalty (θ_{env}) and ethical constraints.

Contribution. No existing framework integrates task exposure, macro dynamics, and skill complementarity into institution-specific recommendations. Prior work operates at occupation-level granularity, missing within-occupation heterogeneity. This synthesis grounds segment-level exposure in Embodied Cognition and optimizes curriculum under complementarity constraints.

2. Case Selection: Careers, Segments, and Institutions

2.1. Career Selection: Spanning the Digitalization Spectrum

This paper selects three career segments spanning the digitalization spectrum:

Library/Stock Music Producer (Arts). Professionals creating functional background music for advertisements, games, and content platforms. Output is a digital audio file valued for functional fit; industry projections estimate 60% AI penetration by 2028 [13].

Gameplay Programmer (STEM). Developers specializing in interactive systems requiring both code generation and embodied judgment about player experience. METR [6] found experienced developers using AI tools took 19% longer on complex tasks—the "efficiency paradox."

Full-Service Restaurant Chef (Trade). Culinary professionals exercising real-time sensory judgment (taste, smell, texture). AI serves only peripheral functions without penetrating core value creation.

These segments maximize analytical variance: purely digital (music), hybrid (games), and purely physical (culinary) (as shown in Figure 1).

Justification. These satisfy: (i) data availability; (ii) reform urgency; (iii) GRASP value demonstration—GRASP agrees with ILO on homogeneous occupations (Chef) but refines variation where it matters (Music, Software).

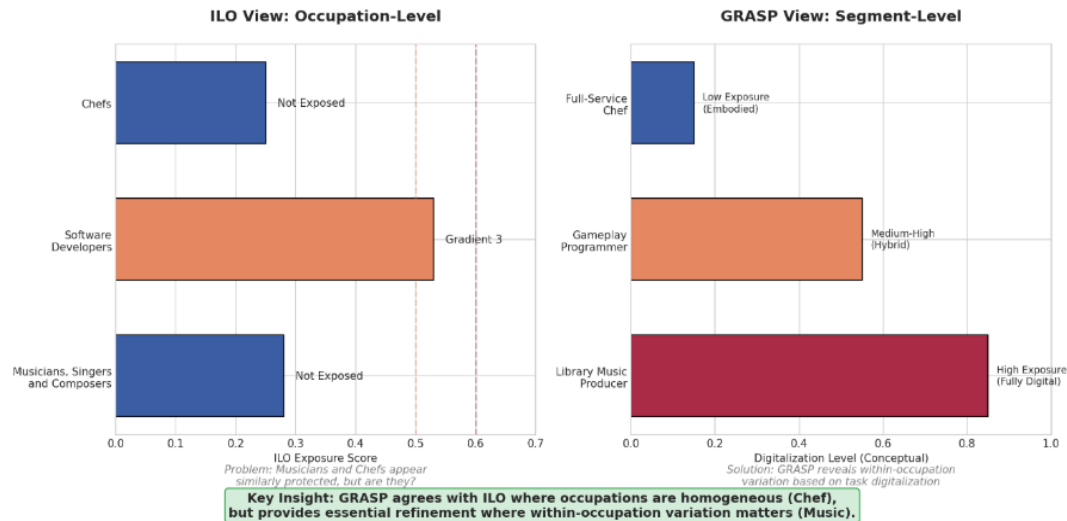


Figure 1. Three career segments spanning the digitalization spectrum, from fully digital (Library Music) through hybrid (Gameplay Programming) to irreducibly physical (Culinary Arts).

Justification. Beyond spanning the digitalization spectrum, these satisfy: (i) data availability—robust empirical ecosystems; (ii) educational reform urgency—distinct reform pressures; (iii) GRASP value demonstration—GRASP agrees with ILO where homogeneous (Chef) but provides essential refinement where variation matters (Music, Software).

2.2. Institutional Anchoring

For each segment, this study identifies a leading institution, as shown in Table 1:

Table 1. Institutional anchoring for each career

Career Segment	Institution	Program	Type
Library Music Producer	Berklee College of Music	Music Production & Engineering	Private Conservatory
Gameplay Programmer	USC	USC Games (B.S. CS + Games)	Research University
Full-Service Chef	Culinary Institute of America	Culinary Arts	Trade School

These institutions align with GRASP's predictions: high-exposure careers require aggressive curriculum transformation, hybrid careers balanced integration, and physical-sanctuary careers conservative stability [14–16] (as shown in Figure 2).

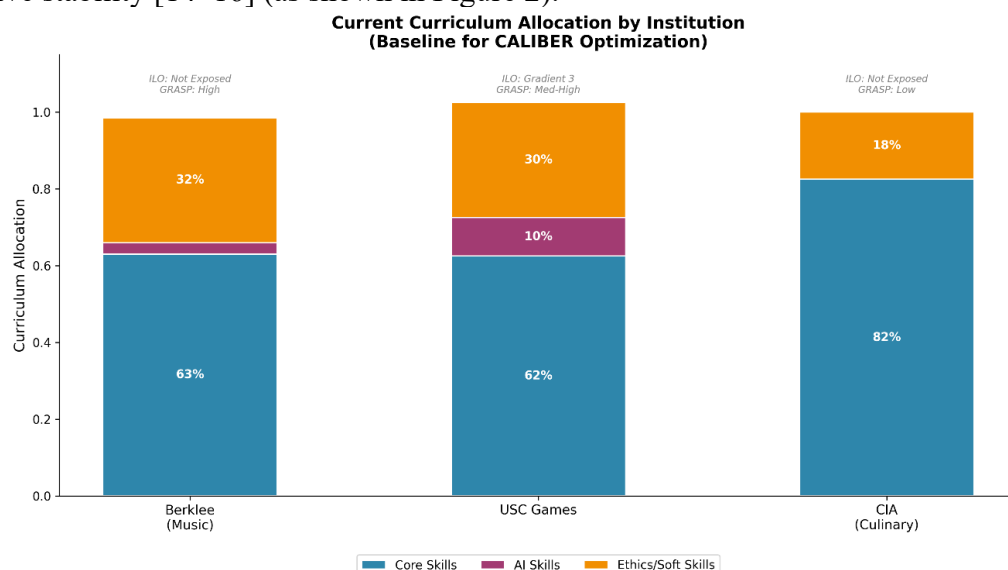


Figure 2. Current curriculum allocation. CIA devotes the largest share to core hands-on skills, Berklee emphasizes core music/production, and USC balances CS fundamentals with general education. AI-specific curriculum is minimal at all three as of 2025.

3. Predicting Labor Market Trajectories Under AI Disruption

This section presents the **PULSE Model**, a dynamic framework translating GRASP insights into quantitative labor demand forecasts. The model synthesizes: (1) the task-based automation framework [2, 3], modeling AI as replacing tasks rather than occupations; and (2) sensory resistance from Embodied Cognition Theory.

3.1. Model Architecture

PULSE operates in two stages: micro-level prediction of AI penetration subject to sensory/physical ceilings, and macro-level conversion into employment changes through three economic forces [4].

Stage 1: Task Penetration (Bounded Logistic Diffusion).

$$E_i(t) = \frac{1 - S_i}{1 + e^{-k \cdot (t - t_{mid})}}$$

Where $S_i \in [0,1]$ is the Sensory/Physical Resistance Coefficient, k is the AI diffusion rate (year^{-1}), and t_{mid} is the inflection point (year 5 of the 12-year horizon). The asymptote is $(1 - S_i)$, not 1: AI cannot breach the physical ceiling—the “embodiment wall.” A chef’s resistance ($S_i = 0.78$) caps penetration at 22%, while a music producer’s ($S_i = 0.19$) permits 81%.

Parameters are calibrated via O*NET v30.1 [18] and industry evidence: for {Library Music, Gameplay, Chef}; demand elasticity [19–21]; verification cost [6].

Stage 2: Labor Demand Evolution (Master Equation).

Building on [2, 3], the model treats employment change as three competing forces:

$$\frac{\Delta L_t}{L_{t-1}} = \underbrace{-\beta \sum w_i \Delta E_i(t)}_{\text{Displacement}} + \underbrace{\rho \sum w_i \Delta E_i(t)}_{\text{Reinstatement}} + \underbrace{\eta \cdot \Delta \ln Y_t}_{\text{Productivity}}$$

- (A) Displacement ($-\beta$): Direct labor demand reduction as AI automates tasks. $\beta = 0.65$ from [2].
- (B) Reinstatement ($+\rho$): New human tasks catalyzed by AI-driven reorganization. Scenario-dependent, reflecting uncertainty.
- (C) Productivity ($+\eta \cdot \Delta \ln Y$): AI lowers costs, prices drop, demand expands. Derived from Hulten’s Theorem [4]: $\Delta \ln TFP_t = \bar{\pi} \cdot \sum_i w_i \Delta E_i(t)$, where $\bar{\pi} = 0.27$. GDP growth converts via capital share $s_K = 0.37$ [17].

Verification Cost Adjustment. This paper introduces V_i , so the effective productivity contribution is:

$$\text{Productivity Gain}_i = E_i(t) \cdot (1 - V_i)$$

For Gameplay Programmers, $V_i = 0.19$ directly measured by METR [6] as productivity decrease on complex tasks. This explains why AI assistance can slow down experts—the “Efficiency Paradox.”

3.2. Three Futures: Scenario Analysis

Gen-AI is in its initial explosive phase; long time-series data is unavailable. This paper defines three scenarios grounded in an **Inverted-U Hypothesis**: the relationship between AI evolution speed (k) and new task creation (ρ) is non-monotonic. At moderate speed, displacement pace allows human adaptation; at extreme speed, the “Red Queen Effect” suppresses reinstatement as new tasks are automated immediately (as shown in Table 2).

Table 2. Three scenario definitions for AI evolution

Scenario	k	ρ	Interpretation
A: Stagnation	0.05	0.20	AI constrained; weak complementarity
B: Symbiosis	0.15	0.50	Optimal complementarity; hybrid roles flourish
C: Singularity	0.40	0.30	Rapid evolution; Red Queen suppresses reinstatement

$k_{med} = 0.15$ reflects McKinsey surveys showing enterprise AI adoption rose from 50% (2022) to 88% (2025) [22, 23].

3.3. Results and Interpretation

3.3.1 Task Penetration Curves

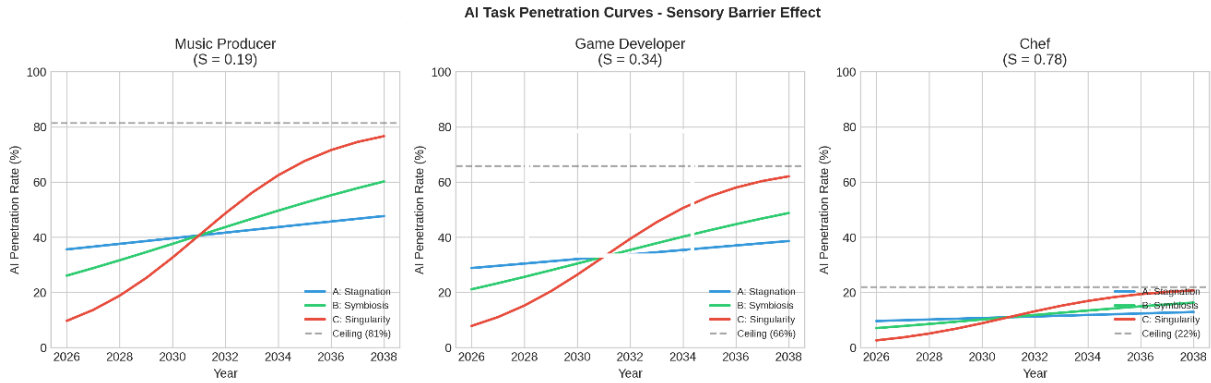


Figure 3. AI Task Penetration showing the sensory barrier effect. Dashed lines mark penetration ceilings ($1 - S_i$). Music Producer (ceiling 81%) faces aggressive penetration; Chef (ceiling 22%) is protected by the “embodiment wall.”

As shown in Figure 3 and Table 3, final-year penetration (2038) is:

Table 3. AI task penetration rates by scenario (2038)

Occupation	Stagnation	Symbiosis	Singularity
Music Producer	48%	60%	77%
Game Developer	39%	49%	62%
Chef	13%	16%	21%

3.3.2 Employment Trajectories

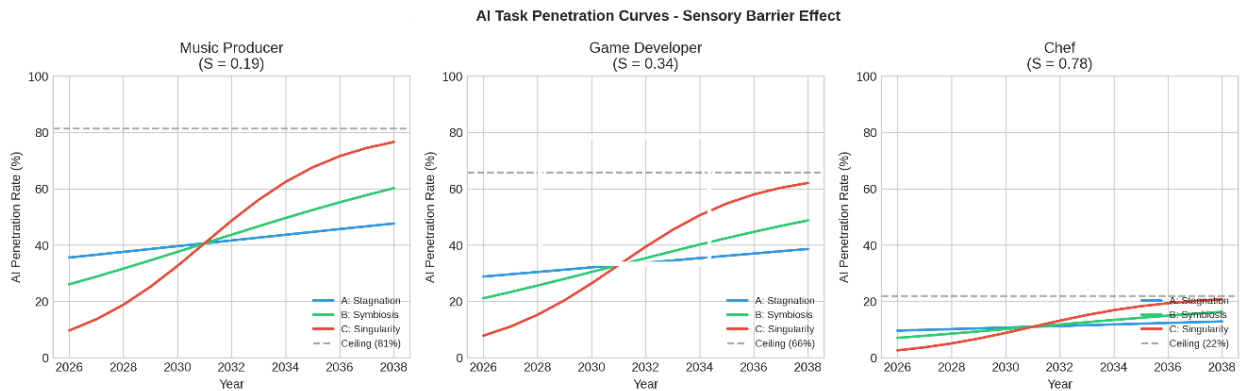


Figure 4. Employment index trajectories (2026=100). Game Developer shows strongest growth potential under Symbiosis (driven by $\eta = 1.8$). Chef remains stable. Music Producer shows moderate growth under Symbiosis but is scenario-sensitive.

As shown in Figure 4 and Table 4, employment index (2038) is:

Table 4. Employment index by scenario (2026=100)

Occupation	Stagnation	Symbiosis	Singularity
Music Producer	100.2	111.2	107.8
Game Developer	101.7	114.0	116.0
Chef	99.5	101.4	99.1

Key finding: Under Symbiosis, all three occupations show stable or growing employment.

4. Aligning Curriculum with a Shifting Labor Market

With labor market trajectories established, this paper addresses: How should programs restructure curricula to maximize graduate viability? This section presents the CALIBER Model.

4.1. Design Philosophy: Skills as Complements, Not Substitutes

CALIBER’s central insight: skills are complements. A graduate mastering core skills but lacking AI literacy is poorly prepared; one with AI proficiency but no domain fundamentals lack foundation. This motivates a Cobb-Douglas viability function:

$$V(\mathbf{w}, E_t) = w_{\text{core}}^{(1-E_t)} \cdot w_{\text{AI}}^{E_t} \cdot w_{\text{ethics}}^C$$

Where $\mathbf{w} = [w_{\text{core}}, w_{\text{AI}}, w_{\text{ethics}}]$ sums to 1, E_t is net AI penetration from PULSE, and $C = 0.30$ is a universal utility constant. Equivalently maximizing:

$$\ln V = (1 - E_t) \cdot \ln(w_{\text{core}}) + E_t \cdot \ln(w_{\text{AI}}) + C \cdot \ln(w_{\text{ethics}})$$

The parameter $C = 0.30$ reflects Deming [9] and Heckman and Kautz [10] finding soft skills account for 25–35% of wage variance.

4.2. Optimization Framework

CALIBER solves a constrained nonlinear program (SLSQP) maximizing $\ln V$ subject to:

1. Normalization: $w_{\text{core}} + w_{\text{AI}} + w_{\text{ethics}} = 1$
2. Accreditation Floor: $w_{\text{core}} \geq w_{\text{min}}$ (Berklee/USC: 0.50; CIA: 0.60)
3. Ethics Floor: $w_{\text{ethics}} \geq 0.10$
4. Faculty Inertia: $|w_k(t) - w_k(t-1)| \leq \Delta_{\text{max}}$

The faculty inertia constraint (Δ_{max}) captures institutional “speed limits.” The analysis tests: Conservative (0.05), Moderate (0.10, baseline), and Aggressive (0.20). Initial conditions (2025): Berklee (0.87, 0.03, 0.10), USC (0.80, 0.10, 0.10), CIA (0.88, 0.02, 0.10).

4.3. Differentiated Institutional Strategies

Under Scenario B (Symbiosis), the optimal curriculum allocations are as shown in Figure 5:

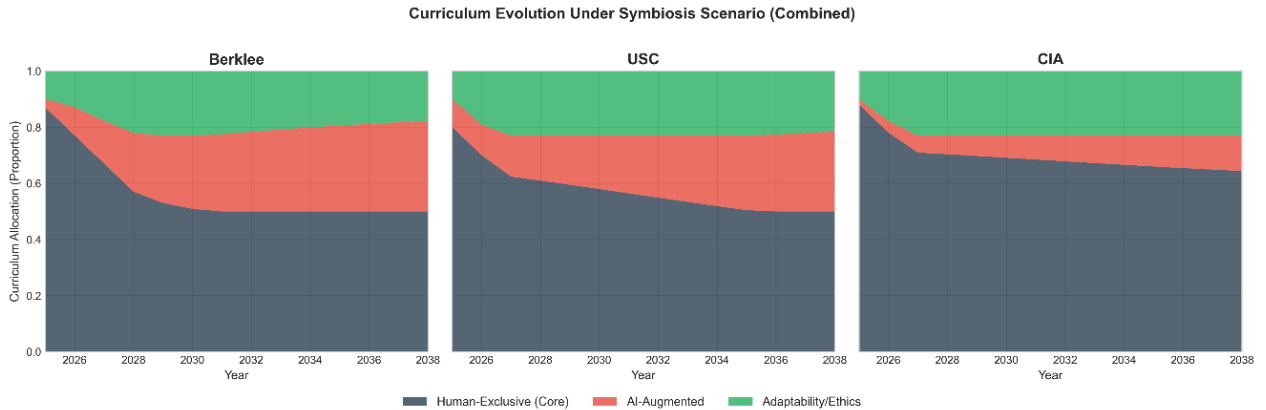


Figure 5. Optimal curriculum allocation trajectories under Scenario B (Symbiosis) for all three institutions. Shaded bands indicate constraint-binding regions.

Berklee: Aggressive Transformation. With highest penetration ($E_t \rightarrow 0.54$), core skills decline from 87% to the accreditation floor of 50%, AI grows from 3% to 32%, ethics rises to 18%. By ~2030, the accreditation floor binds.

USC Games: Balanced Integration. Moderate penetration ($E_t \rightarrow 0.40$) tempered by verification costs. Core CS declines from 80% to 50%, AI grows to 28%, ethics to 22%.

CIA: Conservative Stability. Culinary arts remain largely immune ($E_t < 0.17$). Core skills remain at 64%, modest AI allocation of 13% for back-of-house optimization, ethics at 23%.

4.4. Enrollment and Policy Recommendations

4.4.1 Enrollment Size

Table 5. Optimal curriculum allocations (2038) under Scenario B

Institution	E_t (2038)	w_{core}	w_{AI}	w_{ethics}	Strategy
Berklee	0.54	0.50	0.32	0.18	Aggressive pivot
USC	0.40	0.50	0.28	0.22	Balanced integration
CIA	0.16	0.64	0.13	0.23	Conservative stability

Inertia Sensitivity. As shown in Table 5, under Conservative inertia, Berklee cannot reach optimal AI allocation—becoming "reform-limited." This implies: high-exposure institutions should adopt aggressive reform timelines early.

Recruitment follows naturally from curriculum positioning: Berklee redirects applicants toward AI-curation tracks; USC expands interdisciplinary pipelines; CIA maintains stable enrollment with craft-differentiation marketing.

5. Beyond Employability: Environmental, Ethical, and Cognitive Dimensions

Employment demands are not the only measure of institutional success. This section extends the optimization framework with penalties capturing environmental and ethical costs.

5.1. Extending the Objective

$$J_{\text{ext}} = \underbrace{(1 - E_t)\ln(w_{\text{core}})}_{\text{Base Viability}} + \underbrace{E_t\ln(w_{\text{AI}})}_{\text{Carbon Cost}} + \underbrace{C\ln(w_{\text{ethics}})}_{\text{Model Collapse Risk}} - \theta_{\text{env}} \cdot w_{\text{AI}} - \theta_{\text{eth}} \cdot \max(0, w_{\text{AI}} - 0.4)$$

Environmental Penalty (θ_{env}). Every unit of AI curriculum incurs energy cost through compute resources [12].

Ethical Penalty (θ_{eth}). Triggers only when $w_{\text{AI}} > 0.40$, representing the Model Collapse Threshold [11].

This section explores four policy scenarios (as shown in Table 6):

Table 6. Policy scenario definitions for the extended objective

Scenario	θ_{env}	θ_{eth}	Interpretation
Baseline	0.0	0.0	Pure market forces
Green Campus	0.2	0.0	High environmental priority
Human Guardian	0.0	0.3	Prioritize human knowledge preservation
Balanced Responsible	0.1	0.15	Moderate compromise

5.2. Results: Smooth Trade-offs

Under Cobb-Douglas formulation, environmental constraints produce smooth trade-offs, as shown in Table 7:

Table 7. AI curriculum allocation under Baseline vs. Green Campus policy

Institution	Baseline w_{AI}	Green Campus w_{AI}	Change
Berklee	0.322	0.308	−4.3%
USC	0.284	0.266	−6.3%
CIA	0.125	0.110	−12.0%

The institutional hierarchy is preserved under all four policy scenarios, as shown in Figure 6.

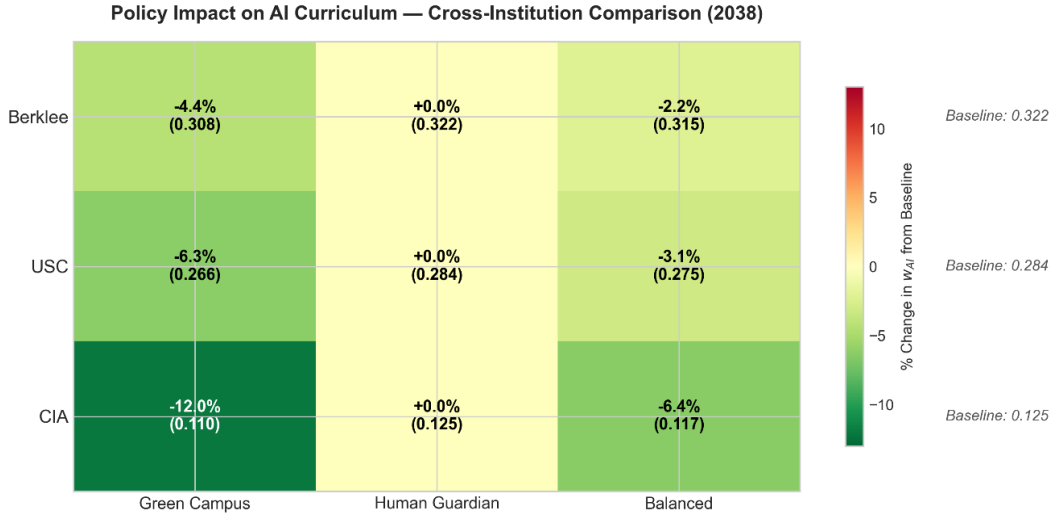


Figure 6. Multi-dimensional policy comparison across institutions. The institutional ranking and relative curriculum allocations remain stable across all policy scenarios.

5.3. The Human-in-the-Loop Necessity

Model Collapse [11] implies that if all content creation is delegated to AI, the knowledge ecosystem destabilizes. Therefore:

- Institutions must maintain authentically human-generated knowledge supply.
- “Human-Exclusive” curriculum is a structural requirement for AI ecosystem health.
- Cobb-Douglas naturally supports this: $\ln(w_{\text{core}})$ always receives positive allocation.

This provides quantitative foundation for the ethical argument that institutions should not abandon human-centered pedagogy.

6. Generalizing Across the Occupational Landscape

This section presents the **COMPASS Framework**, demonstrating that the findings generalize to any occupation.

6.1. The Two-Parameter Generalization Space

An occupation’s optimal educational strategy is determined by two orthogonal factors:

- Sensory/Physical Resistance ($\bar{S}$): Protection from AI due to embodied requirements (determines penetration ceiling).
- Demand Elasticity (η): Market responsiveness to AI productivity gains (determines whether penetration helps or hurts employment).

Zone boundaries derive from constraint hierarchies, as shown in Table 8:

$$Z(\bar{S}, \eta) = \begin{cases} \text{Sanctuary} & \text{if } \bar{S} > 0.7 \\ \text{Pivot} & \text{if } \bar{S} < 0.3 \\ \text{Augmentation} & \text{if } 0.3 \leq \bar{S} \leq 0.7 \text{ and } \eta > 1.0 \\ \text{Pivot} & \text{if } 0.3 \leq \bar{S} \leq 0.7 \text{ and } \eta \leq 1.0 \end{cases}$$

Table 8. COMPASS strategic zone definitions

Zone	Criteria	Representative	Strategy
Sanctuary	$\bar{S} > 0.7$	Chef, Nurse, Electrician	Preserve Craft
Augmentation	$0.3 \leq \bar{S} \leq 0.7, \eta > 1.0$	Game Dev., UX Designer	AI Integration
Pivot	$\bar{S} < 0.3$ or mod. $\bar{S}, \eta \leq 1.0$	Music Prod., Copywriter	Brand Differentiation

A key finding is the “Identity Crisis” condition: even with high elasticity, if $\bar{S} < 0.3$, the occupation enters Pivot Zone. The Music Producer ($\bar{S} = 0.19$, $\eta = 1.2$) illustrates this—despite elastic demand, AI performs over 80% of core tasks, fundamentally redefining the human role.

6.2. The Career Strategy Phase Diagram

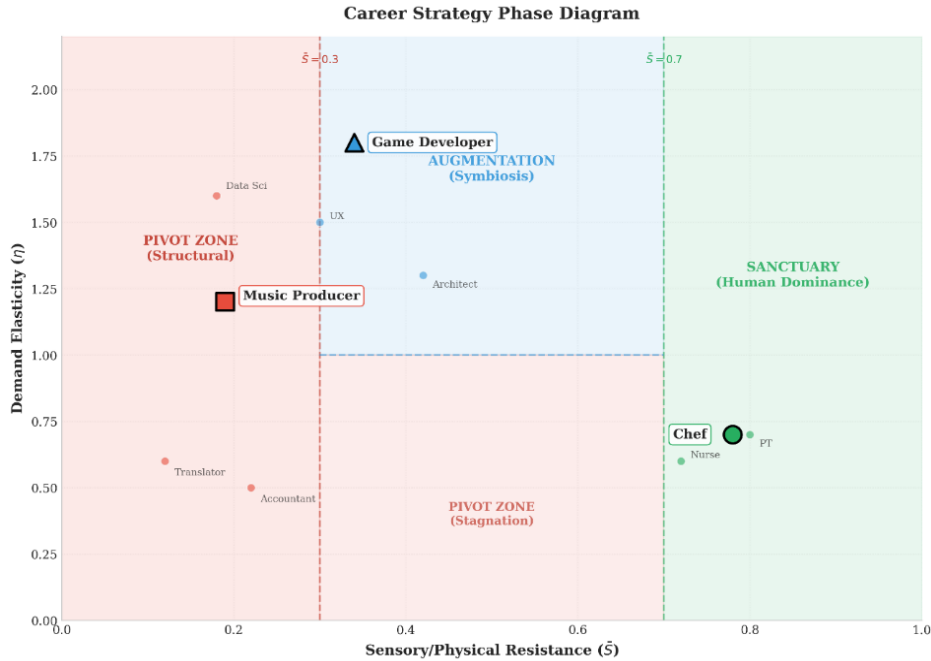


Figure 7. Career Strategy Phase Diagram. Three strategic zones emerge: Sanctuary (green), Augmentation (blue), and Pivot (red). The core occupations anchor different zones, demonstrating the framework captures occupational diversity.

Selected classifications (as shown in Figure 7 and Table 9):

Table 9. Selected occupations classified by COMPASS

Occupation	$\bar{S}$	η	Zone	Strategy
Physical Therapist	0.80	0.7	Sanctuary	Preserve Craft
Registered Nurse	0.72	0.6	Sanctuary	Preserve Craft
Electrician	0.75	0.7	Sanctuary	Preserve Craft
UX Designer	0.30	1.5	Augmentation	AI Integration
Architect	0.42	1.3	Augmentation	AI Integration
Data Scientist	0.18	1.6	Pivot	Differentiate
Translator	0.12	0.6	Pivot	Differentiate
Copywriter	0.15	0.8	Pivot	Differentiate

Zone membership predicts strategy: All Sanctuary occupations share maintaining dominant core skills with modest AI; all Pivot occupations require highest AI allocation for curation and verification.

7. Conclusion

Through the PULSE model, this study demonstrates that employment trajectories under AI disruption depend on the interaction of displacement, reinstatement, and productivity—high exposure does not automatically entail job losses. CALIBER translates these forecasts into differentiated curriculum strategies: aggressive AI-curation transformation for Berklee, balanced verification-centric integration for USC Games, and craft-preserving conservatism for the Culinary Institute. Beyond employability, environmental and ethical trade-offs are smooth rather than discontinuous, while institutional inertia naturally safeguards against Model Collapse. COMPASS generalizes these

findings to any occupation via the strategy space, classifying careers into Sanctuary, Augmentation, and Pivot zones with systematic educational responses. For institutional leaders: programs in Sanctuary should preserve craft pedagogy; those in Pivot must transform aggressively; those in Augmentation should integrate AI as a tool while maintaining irreducible human judgment. For policymakers: accreditation frameworks must permit—and in high-exposure sectors, require—accelerated curriculum adjustment cycles. The question "To Gen-AI, or Not to Gen-AI?" admits no universal answer; it depends on task digitizability, market elasticity, and the pace of reinstatement.

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