Rethinking Talent Cultivation in the Age of Artificial Intelligence: A Theoretical Framework Based on Capability Reconstruction

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Abstract. The rapid advancement of Artificial Intelligence has fundamentally reshaped the logic of talent cultivation. Traditional education systems, which primarily emphasize knowledge accumulation and cognitive training, are increasingly challenged by intelligent technologies capable of performing routine analytical, informational, and procedural tasks. Against this background, this paper develops a theoretical framework of capability reconstruction to explain how talent cultivation should be redesigned in the age of AI. The study conceptualizes talent capability as a multidimensional portfolio composed of cognitive capability, digital capability, social-emotional capability, and innovative capability. Building on this framework, a capability reconstruction optimization model is constructed to analyze how AI penetration changes the relative returns to different capabilities and influences institutional training strategies. To further clarify the dynamic implications of the model, simulation analysis is conducted to examine capability revaluation, institutional transformation thresholds, and equilibrium zones under alternative AI scenarios. The results indicate that the relative return to routine cognitive capability declines as AI penetration increases, while digital capability, innovative capability, and social-emotional capability become increasingly valuable. In addition, institutional transformation depends jointly on technological pressure and reform cost, leading to the coexistence of traditional, transitional, and reconstruction equilibria. The findings suggest that the key challenge of talent cultivation in the AI era is not merely the adoption of AI tools, but the strategic reconstruction of capability structures. This study contributes to the literature by extending human capital theory from accumulation logic to reconstruction logic and by providing a new analytical perspective for educational transformation in intelligent societies.

Keywords: Artificial Intelligence; Talent Cultivation; Capability Reconstruction; Human Capital; Educational Transformation; Simulation Analysis

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1 Introduction

The rapid advancement of Artificial Intelligence has initiated a profound restructuring of modern economies, labor markets, and educational systems. Technologies such as machine learning, generative AI, intelligent automation, and large language models are increasingly capable of performing tasks once considered uniquely human, including data analysis, content generation, pattern recognition, decision support, and personalized interaction. As AI systems continue to diffuse across industries, the boundary between human capability and machine capability is being fundamentally redrawn (Tokunova et al., 2023[1]). This transformation has generated both opportunities and uncertainties for talent cultivation systems worldwide.

For decades, conventional education models were largely built upon the logic of knowledge accumulation. Individuals acquired disciplinary knowledge, technical expertise, and standardized credentials in order to improve productivity and labor market competitiveness. This paradigm was broadly consistent with traditional human capital theory, which views education as an investment that enhances workers' productive capacity. However, the accelerating deployment of AI has weakened the stability of this framework. When machines can increasingly replicate routine cognitive operations, store vast knowledge instantly, and support analytical decision-making at near-zero marginal cost, the economic value of mere knowledge possession declines substantially (Faulconbridge et al., 2025[2]).

As a result, talent cultivation in the AI era can no longer be understood simply as the transmission of knowledge from institutions to learners. Instead, it requires a deeper reconstruction of capability structures (Lei et al., 2026[3]). Capabilities such as creative problem-solving, interdisciplinary integration, emotional intelligence, ethical judgment, collaborative intelligence, adaptive learning, and human–AI coordination are becoming increasingly central. In this sense, the core challenge for education is shifting from "how to teach more knowledge" toward "how to cultivate more resilient and complementary human capabilities."

This shift is particularly significant because AI simultaneously exerts two opposing forces on human talent. On the one hand, AI substitutes for certain routine manual and cognitive tasks, reducing demand for some traditional skills. On the other hand, AI complements human workers by enhancing productivity, expanding innovation potential, and creating new occupational categories (Wu et al., 2026[4]). . Therefore, the impact of AI on talent demand is not a simple reduction or expansion effect, but a structural reallocation effect. Some capabilities decline in relative importance, while others rise sharply. Educational institutions that fail to recognize this transformation may continue producing graduates whose skill portfolios are misaligned with future labor market needs (Liu et al., 2025[5]).

Despite the growing relevance of this issue, existing research remains fragmented. A substantial body of literature examines AI adoption, digital literacy, employability, future work skills, or curriculum reform. Yet many studies focus on isolated dimensions rather than offering an integrated theoretical explanation of how talent capability structures should evolve under AI disruption. Existing frameworks often emphasize technological tools or pedagogical innovation, but understate the deeper economic logic of capability redistribution. Similarly, discussions of future skills frequently list desirable competencies without explaining their interdependence, trade-offs, or optimal composition.

This paper argues that the age of AI requires a transition from human capital accumulation theory toward capability reconstruction theory. Rather than treating talent as a fixed bundle of knowledge and skills, talent should be conceptualized as a dynamic portfolio whose internal composition changes with technological conditions. Under this perspective, education systems are not merely providers of instruction, but institutions that continuously reconfigure the relative weight of cognitive, digital, social, and innovative capabilities in response to technological change.

Accordingly, this study develops a theoretical framework based on capability reconstruction. The model proposes that total talent quality is jointly determined by four broad dimensions: cognitive capability, digital capability, social-emotional capability, and innovative capability. AI affects these dimensions asymmetrically. It may partially substitute traditional cognitive functions while simultaneously amplifying digital and innovative returns. Social-emotional capability remains difficult to automate and may therefore become more valuable under widespread automation. The interaction among these dimensions determines the future competitiveness of individuals and the effectiveness of educational systems.

To further clarify these mechanisms, the paper introduces simulation analysis to compare different AI penetration scenarios. By varying the degree of substitution and complementarity generated by AI, the study explores how optimal capability structures shift under low-, medium-, and high-AI environments. This allows the paper to move beyond abstract conceptual discussion and provide analytically grounded implications for curriculum reform, institutional strategy, and long-term talent planning.

The contributions of this paper are threefold. First, it advances the literature by proposing a unified theoretical framework linking AI development with talent cultivation through capability restructuring. Second, it extends traditional human capital theory by emphasizing dynamic reallocation rather than static accumulation. Third, it provides a simulation-based analytical approach that can guide policymakers and educational institutions in redesigning training systems for the AI era.

2 Literature Review and Theoretical Foundation

2.1 Artificial Intelligence and the Changing Logic of Talent Cultivation

The rapid expansion of Artificial Intelligence has fundamentally altered the traditional logic of talent cultivation. In earlier industrial and information eras, education systems were primarily designed to transmit knowledge, standardize skills, and prepare individuals for relatively stable occupational pathways. Under such conditions, the accumulation of disciplinary knowledge and technical proficiency was widely regarded as the core route to employability and upward mobility (Qian et al., 2025[6]).

However, the rise of AI has disrupted this relatively stable relationship between education and labor markets. Intelligent systems are increasingly capable of completing tasks involving data processing, prediction, content generation, language interaction, and decision support (Miao et al., 2025[7]). As a result, many functions previously associated with human expertise are now partially automated. This shift weakens the long-standing assumption that more knowledge accumulation automatically leads to greater labor market value.

More importantly, AI does not simply replace labor; it transforms the structure of valuable human competencies. Capabilities such as creativity, critical thinking, interdisciplinary integration, ethical reasoning, communication, adaptability, and collaboration with intelligent systems are becoming increasingly important (Ni et al., 2026[8]). Therefore, talent cultivation in the AI era should no longer be viewed merely as a process of knowledge transmission. Instead, it must be redefined as a process of capability restructuring that continuously responds to technological change.

This transformation also creates new pressures for educational institutions. Curricula designed for past industrial needs may become outdated, assessment systems based on memorization may lose relevance, and rigid specialization may fail to prepare learners for uncertain career trajectories (Ma and Ding, 2022[9]). Consequently, the challenge is not whether education should adopt AI tools, but whether education can reconstruct its underlying talent development logic.

2.2 Traditional Human Capital Theory and Emerging Limitations

Traditional human capital theory, strongly associated with Gary Becker, has long provided the dominant economic explanation for education and talent development. It views education as an investment that enhances individuals' productivity, income potential, and contribution to economic growth (Awodiji and Naicker, 2024[10]). From this perspective, schooling and training improve labor quality by increasing knowledge, technical skills, and professional competence.

This framework remains influential because it explains many historical patterns of economic development and wage inequality. Higher educational attainment has often been associated with higher earnings, stronger employment prospects, and improved productivity (Kokkinopoulou et al., 2026[11]). Governments and institutions therefore invested heavily in expanding access to education as a means of strengthening national competitiveness.

Nevertheless, the AI era reveals several limitations of this traditional perspective. First, human capital theory often assumes that the returns to education are relatively stable. Yet when technology rapidly changes occupational skill requirements, previously valuable competencies may depreciate quickly. Second, the theory tends to emphasize the quantity of education rather than the internal composition of capabilities. Years of schooling alone may no longer reflect actual competitiveness in an AI-driven labor market. Third, it places limited attention on substitution effects, where intelligent systems directly perform tasks once completed by educated workers.

Thus, the key issue in the AI era is not simply how much human capital individuals possess, but what kind of capabilities that capital contains. Educational expansion without capability renewal may generate credential inflation rather than genuine competitiveness.

2.3 Capability Perspective and the Need for Reconstruction

A broader theoretical lens can be found in the capability approach developed by Amartya Sen. Rather than evaluating individuals solely by income, credentials, or productivity, this perspective emphasizes people's real opportunities to achieve valued goals and function effectively in changing environments (Yoon, 2021[12]).

Applied to talent cultivation, this means educational quality should not be judged only by examination results or short-term employment rates. It should also include the capacity to learn continuously, adapt to uncertainty, cooperate with others, solve complex problems, and exercise ethical judgment (Li and Xue, 2022[13]). These dimensions become especially significant in the context of AI, where occupational pathways are increasingly dynamic and technological disruption is continuous.

The capability perspective is particularly valuable because it shifts attention from static achievement to dynamic potential. In previous eras, talent development often focused on preparing learners for a first occupation. In contrast, the AI era requires preparation for repeated transitions across occupations, industries, and technological systems. Individuals must be able to reconfigure their competencies throughout the life course (Mancaniello and Lavanga, 2024[14]).

For this reason, the concept of capability reconstruction becomes essential. Reconstruction implies that educational systems must periodically reassess which human strengths remain scarce, valuable, and difficult to automate. It also implies that institutions should intentionally cultivate those strengths rather than preserve outdated competency models. In this sense, capability reconstruction is not a temporary reform agenda but a structural requirement of intelligent societies.

2.4 Research Gap and Theoretical Positioning of This Study

Although recent studies increasingly discuss AI in education, digital literacy, employability, future skills, and intelligent teaching systems, the existing literature remains fragmented. Many studies focus on technology adoption at the classroom level, while others examine labor market impacts or digital skill demand. Few studies provide an integrated theoretical explanation of how AI systematically changes the internal structure of talent capability.

Moreover, much of the current discussion identifies lists of desirable future skills without explaining their relationships, trade-offs, or strategic prioritization. Educational institutions face limited time, budgets, and organizational capacity. Increasing emphasis on one competency area may reduce investment in another. Therefore, talent cultivation requires not only skill identification but also a coherent framework for capability allocation.

Another limitation is that many existing studies remain descriptive. They document the importance of creativity, collaboration, or digital competence, but do not explain why these capabilities rise in importance under AI conditions or how institutions should redesign training systems accordingly. Without stronger theoretical foundations, policy recommendations may remain superficial.

To address these gaps, this study develops a capability reconstruction framework for the AI era. The central argument is that talent should be understood as a dynamic portfolio composed of multiple interrelated capabilities whose relative value changes with technological conditions. AI may reduce the scarcity of some traditional cognitive functions while increasing the value of digital, innovative, and social-emotional competencies. Therefore, the mission of education is no longer simple capability accumulation, but continuous capability rebalancing.

Based on this theoretical positioning, the next chapter develops a formal analytical model explaining how AI reshapes capability composition and how educational institutions can optimize talent cultivation strategies under different technological scenarios.

3 A Capability Reconstruction Optimization Model

3.1 Model Rationale and Analytical Premise

To explain how talent cultivation should be redesigned in the age of Artificial Intelligence, this study develops a capability reconstruction optimization model. The model is built on the premise that educational institutions no longer operate under stable technological conditions. Instead, they face an environment in which the relative value of human competencies changes continuously as AI diffuses across industries, occupations, and organizational systems. Under such circumstances, traditional education models based primarily on knowledge accumulation and disciplinary specialization become increasingly insufficient.

The model further assumes that talent is inherently multidimensional. Individual competitiveness is not determined by a single form of intelligence or technical skill, but by a portfolio of complementary capabilities. These capabilities jointly shape employability, adaptability, productivity, and long-term development potential. At the same time, institutions face scarcity constraints. Curriculum time, faculty resources, infrastructure investment, and organizational reform capacity are limited. As a result, schools cannot maximize every capability simultaneously and must instead make strategic allocation decisions.

Accordingly, talent cultivation in the AI era becomes an optimization problem. Institutions must determine how to reallocate educational resources across multiple capability dimensions in order to maximize future talent quality under technological uncertainty. This logic forms the basis of the formal model presented below.

3.2 Structure of Talent Capability

This study conceptualizes talent capability as consisting of four broad dimensions: cognitive capability, digital capability, social-emotional capability, and innovative capability. Cognitive capability refers to reasoning ability, disciplinary understanding, analytical thinking, and complex judgment. Digital capability includes AI literacy, data competence, technological interaction, and digital tool integration. Social-emotional capability includes communication, teamwork, empathy, leadership, and ethical awareness. Innovative capability refers to creativity, opportunity recognition, interdisciplinary synthesis, and problem framing.

Total effective talent capability is represented as:

$$T = \omega_1 C + \omega_2 D + \omega_3 S + \omega_4 I \tag{1}$$

where T denotes overall talent capability, C denotes cognitive capability, D denotes digital capability, S denotes social-emotional capability, and I denotes innovative capability. The coefficients ω_1, ω_2, ω_3, ω_4 represent the relative contribution of each capability to talent competitiveness.

To preserve internal consistency, the weights satisfy:

$$\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1 \tag{2}$$

Under traditional educational systems, cognitive capability often occupies the largest share because formal schooling historically rewarded examination performance, technical knowledge, and analytical proficiency. However, the rise of AI changes this distribution by altering the scarcity and market value of different human strengths.

3.3 AI-Induced Capability Revaluation Mechanism

AI affects talent capability through both substitution and complementarity channels. First, intelligent systems can increasingly perform repetitive information-processing and standardized analytical tasks. This weakens the relative return to some forms of routine cognition. Second, AI complements workers who can effectively use intelligent tools, interpret outputs, generate new ideas, and coordinate human–machine collaboration. Third, as automation expands, social trust, communication, leadership, and ethical judgment become more valuable because they remain comparatively difficult to automate. To maintain analytical tractability, Equations (3)–(6) adopt a simplified linear specification to capture the baseline direction of AI-induced capability revaluation. This formulation does not imply that the real-world relationship between AI penetration and capability returns is strictly linear. Rather, it serves as a stylized representation of the dominant substitution and complementarity mechanisms under AI diffusion.

Let $A \in [0,1]$ represent the intensity of AI penetration. As A increases, the relative weights of capabilities evolve dynamically.

The return to cognitive capability becomes:

$$\omega_1 = \omega_1(1 - \alpha A) \tag{3}$$

where $\alpha > 0$ measures the substitution effect of AI on traditional cognition.

The return to digital capability becomes:

$$\omega_2 = \omega_2(1 + \beta A) \tag{4}$$

where $\beta > 0$ captures the complementarity effect between AI and digital skills.

The return to innovative capability becomes:

$$\omega_4 = \omega_4(1 + \gamma A) \tag{5}$$

where $\gamma > 0$ reflects AI's amplification of experimentation, idea generation, and creative recombination.

The return to social-emotional capability becomes:

$$\omega_3 = \omega_3(1 + \theta A) \tag{6}$$

where $\theta \geq 0$ indicates the scarcity premium of human-centered relational capability.

Together, these expressions imply that AI changes not only productivity levels but also the internal hierarchy of valuable capabilities. Educational institutions that fail to adjust to this revaluation process may continue producing graduates whose capability portfolios are misaligned with future demand.

3.4 Institutional Optimization of Talent Cultivation

Educational institutions must decide how to allocate finite resources across the four capability domains. Let x_1, x_2, x_3, x_4 denote institutional investment in cognitive, digital, social-emotional, and innovative training respectively. These investments may include curriculum time, faculty development, digital infrastructure, experiential learning opportunities, and pedagogical reform.

The total resource constraint is:

$$x_1 + x_2 + x_3 + x_4 = B \tag{7}$$

where B denotes the total educational budget. In Equation (7), B denotes the available educational resource envelope within a given decision period. This simplified budget constraint is used to capture the scarcity of institutional resources rather than to assume that educational budgets are permanently fixed. In practice, the value of B may change across periods due to government subsidies, policy support, industry–education cooperation, or external project funding.

Each capability is assumed to increase with investment:

$$C = f(x_1), D = f(x_2), S = f(x_3), I = f(x_4) \tag{8}$$

With positive but diminishing marginal returns. This reflects the realistic idea that initial investment in a neglected capability may yield strong gains, while excessive concentration eventually produces lower additional benefits.

The institution seeks to maximize net talent output:

$$maxU = T - \lambda K \tag{9}$$

where U is institutional utility, K is reform cost, and λ reflects sensitivity to adjustment burdens such as teacher resistance, governance rigidity, and financial pressure.

This formulation implies that even when reform is desirable, some institutions may underinvest because transition costs are too high. Hence, differences in governance flexibility can produce divergent educational outcomes under identical technological shocks.

3.5 Comparative Statics and Strategic Implications

The model generates several important implications. As AI penetration rises, the optimal share of investment in digital capability should increase because digital fluency becomes increasingly necessary across occupations. Similarly, investment in innovation capability rises because AI enhances the productivity of creative experimentation and interdisciplinary problem-solving. Social-emotional capability also retains or gains importance because human interaction, ethical reasoning, and leadership remain difficult to replicate technologically.

By contrast, excessive concentration on routine cognitive training becomes less efficient under high-AI conditions. This does not imply that cognition loses value entirely. Rather, higher-order cognition—critical thinking, synthesis, judgment, and conceptual reasoning—remains essential, while narrow memorization and procedural analysis lose relative priority.

These dynamics suggest that educational institutions should gradually shift from a traditional equilibrium centered on academic standardization toward a reconstruction equilibrium characterized by balanced capability portfolios, stronger digital integration, innovation-oriented pedagogy, and human-centered skill development. Institutions that adapt slowly may experience declining graduate competitiveness, whereas adaptive institutions are more likely to cultivate resilient future talent.

4 Simulation Analysis of Capability Reconstruction under AI Penetration

4.1 Simulation Design and Analytical Strategy

Based on the capability reconstruction optimization model developed in Chapter 3, this section conducts simulation analysis to examine how varying levels of Artificial Intelligence (AI) penetration reshape the structure of talent capability and influence institutional decision-making. Unlike empirical estimation, the simulation is designed to illustrate the internal logic of the theoretical model under controlled parameter settings. Therefore, the simulation results should be interpreted as theoretical illustrations of directional mechanisms rather than as empirical predictions of exact marginal effects.

Specifically, the simulation directly builds on Equations (3)–(6), which describe how AI penetration affects the relative returns to cognitive, digital, social-emotional, and innovative capabilities. In addition, Equation (9) provides the institutional optimization condition under which educational institutions decide whether to undertake capability reconstruction given reform costs.

To ensure analytical clarity, all parameter values are normalized and calibrated based on the functional relationships specified in the model rather than empirical data. This approach is widely adopted in theoretical simulation studies, where the objective is to reveal directional mechanisms rather than to estimate real-world magnitudes. The baseline parameter settings are summarized in Table 1.

Table 1. Baseline Parameters for the Simulation

Parameter	Meaning	Value
ω_1	Initial return to cognitive capability	0.4
ω_2	Initial return to digital capability	0.2
ω_3	Initial return to social-emotional capability	0.2
ω_4	Initial return to innovative capability	0.2
α	AI substitution effect on cognition	0.5
β	AI complementarity effect on digital capability	0.8
γ	AI amplification effect on innovation	0.6
θ	Scarcity premium of social capability	0.3
B	Institutional training resource budget	100

4.2 Capability Revaluation under AI Penetration

This subsection simulates how the relative returns to different capability dimensions evolve as AI penetration increases. The simulation is directly derived from Equations (3)–(6), where AI intensity A affects the weights assigned to cognitive, digital, social-emotional, and innovative capabilities.

Using the calibrated baseline parameters in Table 1, the model generates the capability return trajectories reported in Table 2. The numerical values are normalized representations of the functional relationships and are used to illustrate the dynamic revaluation process implied by the theoretical model.

As shown in Table 2, the return to cognitive capability declines monotonically as AI penetration increases, reflecting the substitution effect described in Equation (3). In contrast, digital capability exhibits the strongest upward trend, consistent with the complementarity effect captured in Equation (4). Innovative capability also increases significantly due to AI-driven amplification of experimentation and idea generation, as specified in Equation (5). Social-emotional capability rises more gradually, reflecting its relative resistance to automation and its increasing scarcity value, as indicated in Equation (6).

Table 2. Simulated Capability Returns under Alternative AI Levels

AI Penetration (A)	Cognitive	Digital	Social-emotional	Innovative
0	0.4	0.2	0.2	0.2
0.25	0.35	0.24	0.215	0.23
0.5	0.3	0.28	0.23	0.26
0.75	0.25	0.32	0.245	0.29
1	0.2	0.36	0.26	0.32

Figure 1 visualizes these dynamics as continuous trajectories. The downward-sloping cognitive curve and upward-sloping digital, innovative, and social-emotional curves provide graphical evidence that AI does not eliminate human capability but systematically reallocates its relative importance. This result is fully consistent with the theoretical prediction of capability revaluation in Chapter 3.

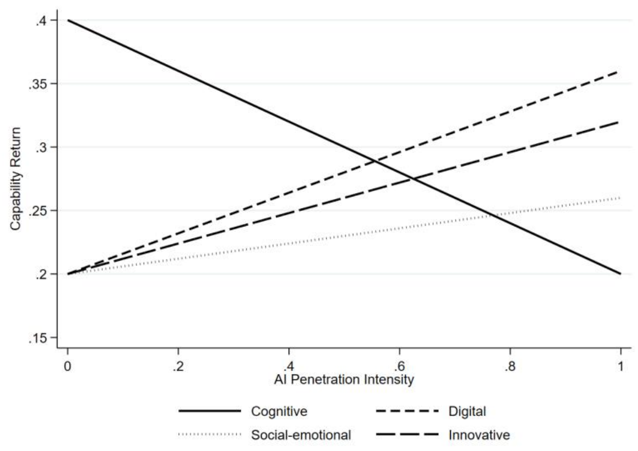

Fig. 1. Capability Revaluation under AI Penetration

4.3 Institutional Transformation Thresholds

This subsection extends the analysis by incorporating institutional reform cost into the decision-making framework. According to Equation (9), educational institutions undertake capability reconstruction only when the net utility of reform is positive, that is:

$$Expected\ Gain\ from\ Reconstruction > Reform\ Cost$$

Based on this condition, the simulation evaluates how AI penetration affects the likelihood of institutional transformation under different cost scenarios. The values reported in Table 3 are constructed by applying the model's utility structure and normalizing the gain function as an increasing function of AI penetration. While the specific numerical values are illustrative, the underlying relationship strictly follows the theoretical condition derived from Equation (9).

As shown in Table 3, when AI penetration is low, expected gains from reconstruction remain insufficient to offset medium or high reform costs. Consequently, institutions tend to maintain traditional training models. However, as AI penetration increases, the expected gain rises nonlinearly, eventually exceeding reform costs and triggering institutional transformation.

Table 3. Institutional Transformation under Different AI Levels

AI Penetration (A)	Expected Gain from	Low Reform	Medium Reform Cost	High Reform	Likely Outcome

	Reconstruction	Cost		Cost	
0.2	18	10	25	40	Limited adjustment
0.4	32	10	25	40	Conditional reform
0.6	47	10	25	40	Transition likely
0.8	63	10	25	40	Strong transformation
1	78	10	25	40	Full reconstruction pressure

Figure 2 illustrates this mechanism using a threshold framework. The intersection points between the gain curves and the cost levels represent the critical AI penetration thresholds required for institutional transition. This figure provides a direct graphical interpretation of the optimization condition specified in the model.

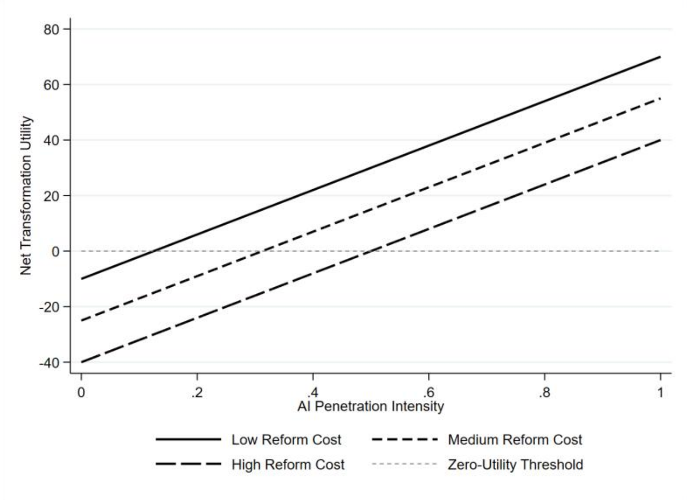

Fig. 2. Institutional Transformation Thresholds

4.4 Equilibrium Zones of Talent Cultivation Systems

Building on the threshold analysis, this subsection introduces a two-dimensional framework combining AI penetration and reform cost to identify different institutional equilibria. This extension is consistent with the optimization structure in Equation (9), where both technological conditions and cost constraints jointly determine institutional behavior.

As shown in Table 4, three equilibrium types emerge from the interaction between AI intensity and reform cost. When AI penetration is low and reform cost is high, institutions remain in a traditional equilibrium characterized by cognitive dominance and knowledge transmission. When both AI penetration and reform cost are moderate, institutions enter a transitional equilibrium, where partial digital reform occurs but legacy structures remain influential. When AI penetration is high and reform costs are manageable, institutions shift toward a reconstruction equilibrium characterized by balanced capability development and capability-oriented education.

Although the model treats educational institutions in an abstract form, institutional heterogeneity is implicitly reflected in differences in reform cost, governance flexibility, resource availability, and organizational adjustment capacity. For example, vocational institutions may face stronger pressure for labor-market responsiveness and practical training reform, whereas research universities may encounter different constraints related to disciplinary structures, research priorities, and academic governance.

Table 4. Institutional Equilibrium Types

Equilibrium Type	AI Penetration	Reform Cost	Capability Structure	Dominant Educational Logic
Traditional equilibrium	Low	High	Cognition-dominant	Knowledge transmission
Transitional equilibrium	Medium	Medium	Mixed capability structure	Partial digital reform
Reconstruction equilibrium	High	Low/Medium	Balanced capability portfolio	Capability optimization

Figure 3 presents these equilibria in a phase diagram. The diagram partitions the space into three regions corresponding to the equilibrium types identified in Table 4. This visualization highlights that institutional transformation is not solely driven by technological progress; it also depends critically on organizational capacity and reform feasibility. Accordingly, the transformation thresholds in the phase diagram should not be understood as uniform across all institutions, but as varying with institutional missions, resource endowments, and reform feasibility.

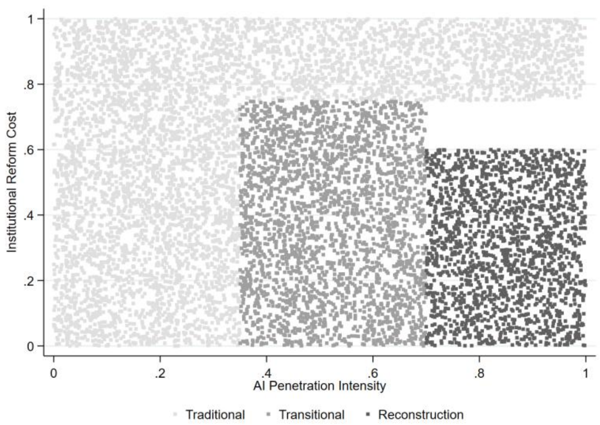

Fig. 3. Institutional Equilibrium Phase Diagram

4.5 Main Insights from the Simulation

The simulation analysis yields several key insights that directly follow from the theoretical model. First, AI penetration systematically changes the relative returns to different capability dimensions, confirming the capability revaluation mechanism derived in Equations (3)–(6). Second, institutional transformation is characterized by threshold effects rather than gradual adjustment, as shown by the utility condition in Equation (9). Third, multiple equilibria may coexist under different combinations of AI intensity and reform cost, implying that education systems do not automatically converge to a single optimal model.

Taken together, these findings demonstrate that the transformation of talent cultivation in the AI era is both technologically driven and institutionally constrained. The results provide strong theoretical support for the central argument of this paper: effective adaptation to AI requires not incremental improvement of existing training models, but a fundamental reconstruction of capability structures.

5 Discussion and Conclusion

This study develops a capability reconstruction framework to rethink talent cultivation in the age of artificial intelligence. Its central argument is that AI does not diminish the value of human talent; rather, it reshapes the internal structure and relative importance of valuable human capabilities. The theoretical model conceptualizes talent as a multidimensional capability portfolio consisting of cognitive, digital, social-emotional, and innovative capabilities. The simulation analysis further suggests that, as AI penetration increases, the relative return to routine cognitive capability tends to decline, whereas digital, innovative, and social-emotional capabilities become increasingly important. However, institutional transformation is not an automatic outcome of technological change. Schools may remain in a traditional equilibrium when reform costs associated with curriculum redesign, teacher retraining, digital infrastructure, and governance adjustment remain high. Therefore, talent cultivation in the AI era depends not only on technological pressure, but also on institutional capacity, resource constraints, and reform feasibility.

This paper contributes to the literature by extending human capital theory from a logic of capability accumulation to one of capability reconstruction, and by linking AI-driven technological change with educational transformation through a unified analytical framework. From a practical perspective, the findings suggest that educational institutions should move beyond the simple adoption of AI tools and redesign curricula around digital fluency, AI literacy, creativity, communication, ethical judgment, and higher-order cognition. Teachers should also shift from knowledge transmitters to capability designers and guides for human–AI collaboration. Nevertheless, this study is limited by its theoretical and stylized modeling approach. The simulation parameters are illustrative rather than empirically estimated, and the results should therefore be understood as a conceptual demonstration of the model's internal logic rather than as precise empirical predictions. Future research may further test and refine the framework using survey data, institutional case studies, or cross-country comparisons, and may examine how different types of education systems reconstruct talent capabilities under AI-driven transformation.

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