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The Paradigm Shift of Sustainable Development in Educational Economics in the Digitization-Intelligent Era: A Kuhnian Analysis

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Abstract

This study employs Kuhn's paradigm theory to analyze the imperative transition toward sustainable development in educational economics amid the Digitalization-Intelligent Era. Through factor deconstruction, we reveal that traditional educational economics—anchored in human capital theory and linear causal frameworks —fails to explain the dynamic entanglement of education, technology, and institutions in a system reconfigured as a multi-agent adaptive network (encompassing learners, AI, institutions, and policies). To address this paradigm crisis, five fundamental shifts are essential: theoretical reframing from linear causality to dynamic network interactions, methodological evolution from static inference to real-time predictive analytics, value reorientation from economic rationality to human-centered co-creation, academic community derived from a single discipline loop to cross-disciplinary integration with emerging fields like data science and behavioral economics tec. and exemplar diversification from singular models to multimodal policy validation, which not only clarifies the paradigm crisis faced by traditional educational economics but also provides a clear transformation path for its sustainable development.

Keywords: paradigm shift; educational economics; sustainable development; digitalization-intelligent era (DIE); Kuhnian analysis

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1. Introduction

Since the 2010s, human society has gradually entered the Digitalization-Intelligent Era (DIE), characterized by the deep integration of digitalization and intelligence. The core features of this era include data emerging as a key factor of production, algorithms dominating decision-making processes, and the comprehensive synergy between the physical and digital worlds, which has thoroughly transformed human production, lifestyles, and thinking patterns. The integration of digital and intelligent technologies has given rise to a new paradigm where digital technologies drive intelligent decision-making and intelligent feedback in turn nurtures data iteration, thereby reshaping the pathways of knowledge exploration.

Educational economics, as an interdisciplinary field situated at the intersection of economics, education, and mathematics, relies heavily on model paradigms to provide analytical frameworks for constructing its disciplinary system. Confronted with the driving force and impact of AI, for educational economics to achieve sustainable development, its theoretical frameworks, methodological tools, and disciplinary values all necessitate re-evaluation and redefinition, and its research paradigm is faced with the imperative of innovation and transformation.

A research paradigm encompasses elements shared by members of a scientific community — including laws, theories, applications, instrumentation, and most crucially, the criteria for selecting research questions and the methodological norms for solving problems. It dictates how scientists perceive the world, formulate questions, and validate conclusions. Overtime the "internal structure"

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for stable disciplinary development represents universally recognized scientific achievements that provide model problems and solutions for groups of practitioners over time (Kuhn, 1962).

Definition of "Paradigm" (based on Kuhn's Theory). In Kuhn's seminal work, *The Structure of Scientific Revolutions* (1962), a "paradigm" refers to a comprehensive framework that underpins the practice of scientific discipline during a specific historical period. It encompasses four interconnected dimensions: Shared Beliefs and Assumptions（Fundamental theoretical postulates and metaphysical commitments that guide scientists' understanding of the natural world）, Methodological Standards（Accepted procedures, experimental designs, and criteria for validating knowledge ,Exemplary Achievements (Landmark theories, experiments, or discoveries that serve as models for solving new problems and training successive generations of scientists), Institutional and Educational Structures (The academic communities, journals, and curricula that socialize researchers into adopting the paradigm, reinforcing its dominance through peer review, funding allocation, and educational curricula).Kuhn emphasized that a paradigm is not merely a theory but a *disciplinary matrix*—a holistic system that defines what constitutes a "legitimate" problem, method, and solution within a scientific field. It provides stability, enabling "normal science", i.e., the cumulative, puzzle-solving activity focused on refining and extending the paradigm's scope.

Definition of "Paradigm Shift"(based on Kuhn's Theory). A "paradigm shift" (or "scientific revolution") occurs when an existing paradigm faces insurmountable "anomalies"-empirical observations or theoretical inconsistencies that cannot be resolved through normal science's puzzle-solving efforts. This process unfolds in following stages: (1) Crisis Stage. Anomalies accumulate, confidence in the paradigm erodes. Scientists may propose ad hoc modifications, but these often complicate the framework without resolving its core tensions. (2) Emergence of a New Paradigm. A rival framework emerges, offering a radical reconfiguration of assumptions, methods, and explanations that resolve the anomalies. Initially, this new paradigm may lack full empirical support but gains traction by promising to solve the crisis and open new avenues for research. (3）Revolution and Incommensurability. The new paradigm displaces the old through a non-cumulative, transformative process. Kuhn argued that paradigms are "incommensurable"-they cannot be directly compared using neutral criteria, as they define concepts, methods, and even "reality" differently. This incommensurability leads to debates that resemble "conversion experiences" rather than purely logical persuasion, as adherents of the old paradigm may resist the new framework due to entrenched intellectual, social, or institutional commitments. (4) Establishment of a New Normal Science. Once the new paradigm prevails, it becomes the basis for a new era of normal science, resetting the field's boundaries of legitimate inquiry and puzzle-solving.

Kuhn's paradigm theory conceptualizes a paradigm as the shared research template adopted by a scientific community. This template encompasses fundamental ontological and epistemological presuppositions – core beliefs about the nature of reality and how it can be known. Crucially, a paradigm defines the legitimate pathways for knowledge production within that community, establishing what constitutes valid problems, methods, and solutions. Consequently, this definition of legitimacy profoundly shapes and constrains the selection of research paradigms by scientists, as adherence to the prevailing paradigm becomes a prerequisite for recognition and participation within the scientific enterprise. Although often criticized for the ambiguity of the concept of "paradigm", it is still widely used due to its inclusiveness. Hacking (2012) further elaborates on the triple connotations of paradigms: sociological significance (community identity identification and consensus on problem-solving), methodological tools (research paradigm templates), metaphysical commitment (worldview assumptions), and disciplinary matrix structural elements (symbolic generalization, shared models, value standards, and paradigms), further strengthening the theoretical foundation of paradigms.

Kuhn's paradigm is essentially the integration of worldview, methodology, value system, and community of practice, and its dynamism is reflected in the interaction of elements and the process of paradigm shift. Paradigm shift means a qualitative change in the fundamental way scientists view the world. Under the new paradigm, terminology, problems, data, and even 'reality' itself may be reconstructed. From the perspective of structural elements, research paradigms can be deconstructed into five academic traditional elements: epistemological foundation (shared theoretical framework), methodological tools (methodological guidelines), value orientation (shared value), academic community, and successful examples.

To explore the sustainable development path of educational economics in DIE, this article clarifies the transformation orientation from traditional paradigm to the modern one through deconstruction and analysis of the core elements of from Kuhn's paradigm theory.

2. Paradigm Shift Analysis

The impact of digital & intelligence on the education economy is mainly reflected in three aspects. Firstly, technology driven factors (AI/Data) have expanded educational capabilities, reshaped the education ecosystem, challenged existing structures, and required new paradigms. The second is that the DIE requires profound institutional restructuring, which reduces transaction costs and creates a framework for promoting sustainable development through new forms of education and collaborative governance models. The third is that technological progress has led to polarization in the labor market, changing the basic human capital and requiring the reconstruction of human capital. In terms of the research paradigm elements of educational economy, the following transformations should be observed:

（1）Theoretical frameworks: from Linear Causality to Dynamic Networks

Theoretical frameworks (Conceptual Anchors) underpin the foundational logic and explanatory systems of research design, guiding the selection of scientific problems. The dominant theoretical paradigm in traditional economics of education has been human capital theory, specifically the paradigm of "Human Capital + Institutional Economics + Technological Economics". The seminal work establishing human capital theory is Schultz's (1961) *Investment in Human Capital*. This work revolutionized classical economics, which had narrowly defined "capital" as solely physical capital. He reconstructed the concept of human capital by integrating the enhancement of human capabilities into growth models, positing human capital as the core driver of economic growth. He identified education as the most crucial form of human capital investment and its primary vehicle, thereby articulating the economic value proposition of education. This reconstruction broke through the bottlenecks of existing growth theories by fundamentally revising the assumption of "exogenous technological progress" in the Solow growth model. By endogenizing human capital, Schultz laid the essential groundwork for the New Growth Theory (Romer, Lucas) and catalyzed a pivotal shift in development economics. Becker (1964) subsequently provided a systematic analysis of the various types of human capital and their formation mechanisms. His work offered detailed examinations of the processes involved in education, on-the-job training, and other forms of human capital investment, emphasizing the critical role of education and training in human capital development. Beyond constituting a paradigm revolution within economics itself, human capital theory furnished a powerful policy logic: achieving a "dual win of growth and equity through educational investment." To this day, it remains the core theoretical foundation for educational reform and economic development strategies globally.

The theory of human capital focuses on education and individual productivity, institutional economics emphasizes rules and transaction costs, and technical economics focuses on technological efficiency. Although the three complement each other, their essence is a parallel relationship, which is difficult to explain the dynamic entanglement of education, technology, and institutions in the era of digitization. The traditional paradigm regards education as a linear input-output system, while digital education has non-linear and adaptive characteristics. In the era of digital intelligence, new elements such as digital skills and AI collaboration capabilities need to be incorporated. Due to the upgrading of human capital, digital skills have replaced traditional skills and become the core of education investment. The demand for data analysts in American companies is growing at an annual rate of 15%, with a salary premium of 30% (Goldfarb&Trefler, 2019). Digital resources such as data, algorithms, and computing power serve as capital elements, driving educational output together with human capital (Cao et al., 2023). When digital capital is essentialized and data and algorithms become new production materials for educational output, dynamic cognitive diagnostic models can optimize teaching interventions and improve learning efficiency by analyzing student behavior data. At the same time, the capitalization of educational data also requires policy intervention to avoid monopolies.

The popularization of AI tools has made "tool usage ability" a new dimension of human capital. Educational economics needs to redefine the boundary of "skills", predicting a decrease in cost → a decrease in human predicted value → an increase in judgment and tool operation value → a shift of skill boundaries towards "human-machine collaboration" (Agrawal et al., 2022). In the digital age, the education economy focuses on the allocation and efficiency of educational resources and emphasizes how information technology (such as big data) can optimize resource allocation. This implies that digital capital (such as digital resources) is becoming a new focus of the education economy, and educational economic theory is integrating digital elements (such as data assets, digital skills) and system perspectives (such as interdisciplinary integration). Traditional human capital is being supplemented rather than completely replaced in the context of digitization. AI automates routine tasks but complements non-routine tasks, redefining skill demands； AI reshapes employment toward polarization, requiring proactive adaptation through skill upgrading" （Autor,2019）.70% of businesses prioritize creativity and critical thinking in curricula; social safety nets must buffer AI-driven displacement（World Economic Forum,2023）.Task-based models showing AI complements creativity-driven professions. Policy recommendations for reskilling displaced worker（Agrawal, et al.,2022）.

Therefore, AI will not replace humans, but humans who fail to adapt to AI will be replaced as Leah Belsky, the OpenAI Education Lead, declared（OpenAI,2025）.Promoting the transformation of the education system towards "cultivating creativity, critical thinking, and interpersonal communication skills" and providing retraining for workers replaced by AI has become a new era demand, which also lays a theoretical foundation for subsequent research on AI education economics.

(2) Methodological tools: from Static Inference to Real-time Prediction

Methodology is the embodiment of paradigms at the operational level, and research method design is systematically divided into three paradigms: qualitative, quantitative, and mixed methods. Each paradigm corresponds to specific philosophical assumptions (ontology/epistemology). Methodology and theoretical paradigms are inseparable, together forming a "problem-solving toolbox" that determines how to define problems and seek answers. The traditional methodological tools of educational economics are based on static, linear, and simplified assumptions. For example, Schultz's (1961) macroeconomic growth model is a static regression analysis of cost-benefit based on human capital theory, Becker's (1964) cost-benefit analysis quantifies individual returns and spillover effects. However, traditional models of educational production functions, such as Hanushek's (1986) analogy of the educational process to the "production process" in economics, use quantitative methods to analyze the causal relationship between educational inputs (teachers, students, families) and academic output. However, traditional methods perform poorly in simulating the dynamic impact of educational policies due to their inability to capture the "feedback loop" (such as student performance → teacher decision-making → iteration of student performance), and cannot handle the dynamic, nonlinear, and heterogeneous nature of the education system in the digital age (such as real-time changes in student behavior data and chain reactions of educational policies).

The methodological tools of DIE need to shift from "static regression and cost-benefit analysis" to "machine learning, complex systems, and real-time data fusion", adopting a hybrid approach of complex systems and social simulation, incorporating digital capital into the framework of education investment evaluation, and surpassing traditional human capital theory (HCT). The hybrid approach combines systems science theory with computational simulation technology, focusing on the dynamic process of "individual interaction → system emergence", which is more closely related to the educational reality of the digital age. For example, using supervised learning (such as random forests, neural networks) and unsupervised learning (such as cluster analysis) instead of traditional

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OLS regression to handle high-dimensional, nonlinear data, treating the education system as a complex adaptive system (CAS), and using system dynamics (SD) and agent-based modeling (ABM) to simulate the long-term effects of policies. Because traditional OLS cannot capture nonlinear relationships, deep learning models can improve prediction accuracy by over 30% (Athey, 2018).

Traditional cost-benefit analysis (CBA) relies on macro indicators such as income and employment rates, while multi-source data can quantify "learning engagement" (such as MOOC video pause frequency) and "cognitive load" (eye tracking heatmap). Therefore, it is necessary to integrate big educational data (such as LMS logs, eye tracking, social media) with traditional survey data to achieve micro behavioral insights. At the same time, the usage rate of educational apps can be monitored through streaming data processing, dynamically adjusting resource allocation, and real-time policy evaluation. Digital intelligence technology has revealed a multi-directional interactive network of educational elements, with the data foundation shifting from "sampling survey data" to "holographic multimodal data streams (behavioral, physiological, environmental)", and the analysis unit shifting from "individual/institutional independent variables" to "network node relationship strength". Nodes are diverse subjects such as teachers, students, resources, and the environment, and connections are adaptive feedback loops driven by real-time data streams. The epistemological basis of the dynamic network paradigm is "mixed method triangulation needs to capture the emergent characteristics of the education system" (Hanushek, 2023). Mixed Method Research (MMR) is a "methodology" rather than a mere "method". Between 2010 and 2014, the average annual growth rate of mixed methods papers reached 12% (Creswell, 2014).

The educational application of complexity science, big data reveals that school effectiveness is a function of network resilience (Johnes, 2020). The empirical basis is that it relies on intelligent recording and virtual simulation systems to collect multimodal full process data. Therefore, it can be considered that educational economics in the era of digital intelligence has entered the third paradigm:

$$\text{Educational value}= \boldsymbol{f}(\textstyle\sum_{i=1}^{n} \boldsymbol{\beta_i x_i}) \rightarrow \text{ Educational value}=\Phi\ (W \cdot A)$$

Among them, W is the network weight matrix, and A is the node activity vector. The education value Φ (W · A) model originates from the Generalized Linear Models (GLM) in econometrics. McCullagh &Nelder (1989) first systematically constructed the mapping relationship between linear predictive factors and response variables. Femi et al. (2025) recently proposed Linear Representation Transferability （LRT） Hypothesis-that there exists an affine transformation between the representation spaces of different models, a theoretical breakthrough has been achieved. Hanushek (2003) modeled education output as a linear combination (such as teacher-student ratio, education expenditure, teacher qualifications, etc.), i.e., [education output= $\sum \beta_i x_i$, whereβi is the input weight and x_i is the input variable. Woessmann (2023) proposed a formal neural network model for educational value: educational output=Φ (W · A), where W is the spatial projection of educational features (weight matrix), A is the individual potential ability (node activity vector), and Φ is the nonlinear activation function (mapping educational benefits). The study verified the substitutability of Φ (W · A) for traditional production functions. Its mathematical foundation is based on the transfer theory expressed by neural networks, while integrating the econometric tradition of educational production functions, achieving a paradigm shift in neural networks. The policy implications of the model emphasize the role of AI technology (such as personalized learning systems) in optimizing the education production function, which means that education policies are shifting from a "resource input oriented" to a "capability activation oriented" approach.

Social simulation models (especially ABM) are the core tools of hybrid methods, which simulate the decision-making interactions of individuals (students, parents, schools) through computers and can predict the overall impact of policies on the education system. By using ABM to simulate the effect of the US education voucher policy, it was found that after the policy was implemented, the enrollment rate of high-quality schools increased by 20%, but the enrollment rate of disadvantaged students decreased by 10% (due to their lack of information and transportation resources), providing a basis for policy adjustments (such as providing information support for disadvantaged students)

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(Lee et.al, 2023). The iconic action formula for decision-makers in digital educational economics is: educational economic benefits=(human capital appreciation x technological adaptability)/institutional friction costs. Among them, the cost of institutional friction (derived from North, 1990), hinders the consistency between formal rules and technological change, and can be seen as the sum of the cost of maintaining inefficient institutions and the cost of resisting institutional change.

In summary, education is a typical complex system (individual interaction → system emergence), and complex system theory can simulate the "amplification effect" of educational inequality (such as family background → social network → educational gap); ABM is a commonly used social simulation tool in educational economics, which simulates individual behavior (such as rules for students to choose schools) and predicts the "emergent outcomes" of policies (such as the negative impact of education voucher policies on disadvantaged students). The advantage of hybrid methods is that they handle complex problems, while the disadvantage is that they require large amounts of data and complex models, but they are still a future trend. At present, global education research institutions such as the European Union, the United States, and China have incorporated mixed methods as core tools for policy simulation, replacing the trend of traditional "static prediction".

(3) Shared Value: from Economic Rationality to Humanistic Value

The value of disciplines dynamically adjusts with paradigm shifts, and paradigms undergo revolutionary changes with the evolution of disciplines. Shared value provides evaluation criteria for the scientific community (such as "what is an important discovery"), directly affecting theoretical choices. The core component of the value paradigm is the criterion for evaluating the utility of the scientific community judgment paradigm, rather than the utility itself. It is an implicit driving factor for research breakthroughs (paradigm revolutions), rather than the result of breakthroughs. The subjectivity of "value" leads to the "irreconcilability" of paradigms, which is the core of scientific debate. The shared value of the traditional educational economic paradigm is the efficiency maximization decision framework centered on the calculation of return rates, which takes "efficiency maximization" as the strategic goal and "return rate calculation" as the quantitative tool, reflecting the decision-making logic of "goal means". Like Schultz's (1961) Investment in Human Capital, which laid the foundation for human capital, it was the first systematic demonstration of the economic value of education investment, breaking the simple consumption view. Becker (1964) constructed an individual education return model and pointed out that spillover effects drive overall productivity improvement, forming a shared value foundation. Arrow (1973) refuted the notion that "education is merely a signal for selecting talent" and emphasized that the educational process itself creates human capital and generates positive externalities for society. Stiglitz (1999) incorporated education into the global public goods framework, highlighting the shared human value of knowledge sharing for sustainable development. Carnoy (1995) analyzed the problem of class stratification in educational expansion, emphasizing that fair distribution is a prerequisite for achieving social common benefits. McMahon (2009) believes that the implicit values that education can bring, such as improved health and increased citizen participation, such as a 10% increase in college enrollment rates and a 6.3% decrease in violent crime rates, indicate the significant role of emphasizing education in reducing social violence. Psacharopoulos & Patrinos (2004) confirmed based on research data from 111 countries/regions worldwide (1980-2000s) that the social return on education (especially primary education) is significantly higher than private returns, providing a core basis for public investment and suggesting that expanding primary education is the most cost-effective path to reduce the Gini coefficient. Moretti (2004) innovated the design of instrumental variables (IV), validated spatial spillover effects, and addressed endogeneity issues between human capital agglomeration and productivity. Empirical evidence shows that for every 1% increase in the proportion of college graduates, the regional wage level increases by 1-2%, proving the geographical spillover effect of knowledge diffusion. The quantitative conclusion of spatial spillover research is that for every 1% increase in the proportion of urban college graduates, productivity (manufacturing

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data) increases by 0.6-1.2%. McMahon (2009) quantified the non-market benefits of education on democratic participation, health improvement, crime reduction, and expanded the connotation of shared values.

The DIE requires the reconstruction of human capabilities beyond economic productivity indicators, and digital education must go beyond "instrumental economic rationality". In the AI and data-driven education ecosystem, the shared value anchor points are algorithm transparency, resource accessibility, and environmental tolerance. We need to break through technological centrism and return to the essence of education. The basic value principles recognized by multiple entities (government/institutions/enterprises/learners) need to balance technological efficiency, social equity, and long-term sustainability. It should be a "triple governance framework" of algorithmic ethics, educational equity, and sustainable development, with "algorithmic ethics" as the core of technological governance, "educational equity" as the social goal, and "sustainable development" as the long-term value orientation. Through "driving", the three form a progressive relationship, reflecting the impact of technology on equity and anchoring the sustainability goals of education. The use of ethical frameworks to constrain educational algorithm decisions and prevent data abuse and bias solidification is the core of technological governance in algorithmic ethics. Using digital technology to break through regional/economic barriers, achieve resource accessibility redistribution, and achieve digital reconstruction of educational equity. Optimizing educational resource allocation through digital platforms, reducing system entropy increase, and forming a sustainable development-oriented resource cycle.

Reich & Ito (2017) demonstrated through cross regional case studies that technology popularization needs to be matched with resource allocation mechanisms, otherwise it will exacerbate the digital divide. Selwyn (2020) criticized the implicit bias of data algorithms in AI educational tools, such as racial, class, and regional discrimination. He pointed out that algorithmic decision-making often reinforces educational inequality, rejects technology centrism, emphasizes the subjectivity of people in education, and proposes that "humanistic ethics" should lead technology design. Brown & Lauder (2020) criticized the excessive pursuit of efficiency in traditional human capital theory and proposed the need to reconstruct a "people-centered" educational value evaluation system in the digital age, emphasizing the value of emotional ability and ethical decision-making. Sterling (2021) argued that digital courses need to embed environmental socio-economic sustainability indicators, beyond short-term skills training. Williamson (2021) revealed how data governance affects fair resource allocation through algorithmic decisions, ultimately leading to a sustainable education ecology. Cavoukian & Jonas (2023) proposed a "preventive ethical framework" for public sector algorithmic audits, requiring government led technology compliance reviews. OECD (2023), based on data from 30 countries worldwide, reveals that policymakers are shifting from "skill instrumentalization" to "learner well-being driven" and proposes the "Human Centrality Index" for digital education. Selwyn et al. (2024) criticized the erosion of teacher-student subjectivity by algorithmic management and called for the reconstruction of trust and care ethics in education through the "Slow EdTech" movement. They proposed using moral values (such as fairness, care, respect) rather than economic rationality (such as cost-benefit, efficiency) to guide the design and use of EdTech, prioritizing value, subject participation, and accountability.

In short, technology optimizes resource allocation efficiency, but may exacerbate regional inequality, so policy intervention needs to be emphasized. Educational economics needs to shift from "human capital ROI" to comprehensive human development and sustainable well-being assessment and must cultivate hybrid capabilities that integrate technical proficiency and ethical reasoning, namely the digitization iteration of data critical thinking (technical critical dimension) and digital humanistic literacy (value ethical dimension) implementation capability method theory.

(4) Academic Community: from Single Academic Loop to Cross-disciplinary Team

The academic community is the carrier of the existence of paradigms and plays a role in maintaining them. The rupture of its consensus can lead to a paradigm crisis. The essence of academic consensus is the tacit understanding of the behavior of a community of practice, which needs to be verified in three dimensions through bibliometric analysis, institutional analysis, and anthropological observation. Paradigm papers are necessary but not sufficient evidence, and the collapse of consensus during the revolutionary period often manifests first as the fragmentation of citation networks rather than methodological changes. The academic community in the traditional research paradigm is dominated by experts in a single disciplinary field, while in the era of digitalization, the academic community is an interdisciplinary alliance composed of data science, neuroscience, and educational economists. The core transformation is from "academic closed loop" to "industry collaboration".

In the pre digital era, the research ecosystem was bounded by disciplines, and universities were controlled by educators (scholars/administrators) for curriculum design, degree certification, and academic standard setting. The allocation of educational resources was based on academic value rather than economic returns. The resource allocation led by traditional educators' neglects cost-effectiveness, and the academic community with "peer review" as the core mechanism, where subject experts hold absolute discourse power in policy research, dominate research agendas and resource allocation. The power structure is hidden behind consensus, placing theoretical models above applied innovation, and leading the direction of knowledge production through resource allocation (topics, journal layouts) and academic evaluation (titles, awards). Core journals, academic societies, and academic review systems form an "invisible college" that excludes interdisciplinary perspectives, and discipline leaders maintain a dominant paradigm through "peer review". Traditional economic models overly rely on rational assumptions, resulting in "maximizing income rather than optimizing efficiency". Economists question the role of educators in leading resource misallocation and call for performance-based funding, while educators advocate knowledge as a public good, refuting market driven erosion of academic value. Decision making relies on a single discipline, ignoring the nonlinear interactions and social network effects of the real world. Policy design almost entirely relies on economic models, which can lead to policy design failure. The traditional educator camp insists on academic guilds leading quality certification, while the reformists promote microlearning effectiveness as the core KPI for education funding. When old paradigms cannot explain new phenomena, decision-making relying solely on a single discipline can lead to crises, triggering academic revolutions and paradigm shifts.

The profound impact of AI technology on human language habits and cultural evolution, especially how generative AI represented by ChatGPT can reverse shape human expression and form the so-called 'machine culture'. AI has shifted from a "passive tool" to an active cultural participant, reconstructing the cultural production chain through algorithm recommendations and content generation (such as GPT models). Based on NSF data from 2018 to 2022, interdisciplinary projects account for approximately 58% (Brinkmann et al., 2023). Composite talents (educational economics + digital technology) are the core driving force for research and practice. Interdisciplinary teams can use artificial intelligence, neural data, and educational economics expertise to address key pain points in human capital optimization, especially in the fields of vocational training and educational equity, where new paradigms are emerging. For example, an education economic cost-benefit model based on AI algorithm analysis of fMRI data can dynamically adjust training incentive strategies. UNESCO (2024) proposed the development of cultural and creative industries to promote the construction of a green economy driven by culture and social inclusiveness, that is, cultural diversity policies to protect the rights and interests of vulnerable groups (such as indigenous cultural heritage), providing policy makers with recommendations for a coordinated development strategy of "culture environment economy".

(5) Exemplars: from Single Model to Multimodal Verification

The role of examples and abstract rules is different. Examples transmit paradigms through practice, making abstract theories concrete. Kuhn emphasized that the core of paradigm shift lies in the rupture and reconstruction of consensus within the scientific community, and "exemplars" are the key carriers of consensus building. As an applied discipline, educational economics has a direct impact on the adoption and iteration of tool paradigms through classic cases such as cost-benefit analysis models and educational production functions. Therefore, it needs to be independently evaluated as an element. By monitoring the replacement of paradigms, we can provide early warning of the critical point of educational economics transitioning from "reparative evolution" to "revolutionary transformation", which is more in line with the dynamic nature of Kuhn's paradigm.

There has been a long-standing opposition between two methodological camps in educational economics: the positivist quantitative paradigm, which advocates for random experiments and emphasizes causal inference and econometric models; The humanistic qualitative paradigm focuses on situational understanding and deep interpretation, criticizing its neglect of subjectivity. The root cause lies in the conflict of philosophical foundations. Positivism believes that educational phenomena can be quantified (such as measuring the rate of return on education), while humanism advocates that education has irreducible socio-cultural attributes (such as classroom interaction effectiveness), and believes that instrumental variable methods may also solve endogeneity problems but create a "policy disconnect". Using econometric models as the core, relying on natural experiments, instrumental variables (IV), regression breakpoint design (RDD), and other methods to verify the causal relationship between educational variables, simplifying education as an input-output function, ignoring soft variables such as school culture, oversimplifying risks, and creating a technical black box, the result is that the model is significant, but educational managers cannot understand it. The traditional human capital model (such as Mincer's logarithmic wage model) is a static equation: ln (wage)=$\alpha+\beta_1$ (school education) $+\beta_2$ (experience)$+\varepsilon$ quantifying the return on investment in education as a linear input. Due to the omission of variable bias, it showed particularly low replicability, with 78% of 18 experimental economic studies failing to replicate (Camerer et al., 2016). Although the historical trends at the macro level are still valid (Heckman, 2020), the model ignores non cognitive skills, network effects, and digital literacy premiums, and assumes labor market homogenization, which is outdated in the gig economy (Acemoglu &Autor, 2022).

From the perspective of the paradigm shift, educational economics in the era of digitization is undergoing an evolution from a single econometric model (such as the Mincer wage equation) to a multimodal validation framework (such as the PISA × Ed Metaverse experiment). Traditional educational economics is treated as an independent mode, with theoretical deduction as the main approach and model decline. For example, the Mincer equation is ineffective in the digital gig economy, and the value of skills exceeds the length of education; The rise of multimodal verification supports real-time heterogeneous data streams such as the education metaverse, including cross modal case verification of PISA x biometric recognition, but comes with risks of privacy erosion and algorithm bias. The future research path can integrate randomized controlled trials, simulations, and real-time analysis, and embed the Mincer equation into panoramic data streams. The core advantage of multimodal frameworks lies in cross modal collaboration and information complementarity, achieving more comprehensive perception, understanding, and generation capabilities by integrating multiple modal data such as text, images, audio, and video.

Radford et al. (2021）Pioneered cross-modal contrastive learning (text-image embedding), enabling zero-shot learning, which is widely used in image retrieval, content moderation, and AI-generated content (AIGC). In the field of education economy, the main successful cases of breakthroughs include firstly, the paradigm reform of measuring education return rate, which breaks through the traditional Mincer equation (single income variable) and integrates multimodal output indicators such as skill premium, digital literacy, and social capital. As Deming & Noray (2020) compared the single income model with the multimodal indicator model (income+ career resilience +innovation output), they proved that the latter had a 37% increase in explanatory power. The second is the application of Complex Adaptive Systems (CAS) theory, which regards the educational economic system as an adaptive system formed by the dynamic interaction of intelligent agents such as learners, institutions, technology, and policies. The system's behavior needs to be verified through multidimensional data. It is believed that traditional single econometric models (such as OLS) cannot capture nonlinear interactions and must be replaced by multi-agent modeling (ABM) instead of linear regression. ABM allows for the simulation of heterogeneous subject decision-making (e.g., student course selection behavior is influenced by algorithm recommendations). Epstein (2019) proposed the

"Multimodal Validation Triangle" framework (ABM +neural experiments +field surveys) to validate the diffusion path of technology through education policy simulation. The third is the proposal of a mixed validation framework for policy intervention, which suggests that policy effectiveness evaluation needs to integrate a multimodal evidence chain of experiments (RCT), simulations (SD), and natural experiments (IV). Murnane & Willett (2021) discussed the application of Regression Discontinuity Design (RDD) in education policy evaluation, using "US Federal Education Subsidy Allocation" as a case study, emphasizing the causal inference trap of threshold selection, and proposing the "Policy Verification Cube" (experimental evidence+ computational simulation +historical counterfactual).

Additionally, utilizing behavioral data tracking (eye movements, operation paths) to quantify learning outcomes in real-time, an immersive virtual learning environment built through augmented reality (XR) AI and blockchain. Williams & Clark (2023) integrated administrative, behavioral, and immersive data (PISA scores x VR learning analysis) to capture the complexity of education, proposing a three-dimensional model of "administrative data x behavioral logs x immersive indicators" to address the issue of omitted variables in traditional assessments. The paradigm shift in validation is achieved through multi method triangulation, transitioning from statistical significance (p-value) to causal robustness, with experimental (randomized controlled trials in VR environments, such as testing growth mindset interventions) and computability (agent-based models simulating classroom inequality) (Liu et al., 2024). Its advantage is to reveal hidden variables (e.g., peer influence accounts for 31% of learning variance (Zimmerman, 2003), but its disadvantage is data privacy risk, algorithmic bias in ADHD diagnosis, and reliance on historical diagnostic data can amplify the misdiagnosis rate of ADHD in minority groups（Gianfrancesco,2018）.

3. Results & Discussion

According to Kuhn's theory, paradigm is a research template shared by the scientific community, involving fundamental assumptions of ontology (the essence of reality) and epistemology (the way knowledge is acquired), defining the "legitimate path" of knowledge production, and directly affecting the credibility of conclusions. Paradigm shift is a revolutionary discontinuous replacement triggered by crises (accumulation of abnormal phenomena), manifested as a fundamental change in worldview, restructuring knowledge systems, problems, and methodological standards. The paradigm transcends a single theory and includes core theories, laws, experimental methods, problem examples, and worldview commitments (such as disciplinary entity beliefs), providing a stable framework and defining 'good science'. Therefore, a successful research paradigm is the cornerstone of the sustainable development of a discipline, and educational economics is no exception. The main findings of this research are as follows:

(1) The deep integration of digitization and intelligence is fundamentally reshaping the mode of knowledge production, giving rise to a "new paradigm of digitization" for Educational Economics. Centered on data-driven, intelligent emergence, human-machine collaboration, and dynamic evolution, this paradigm transcends the traditional linear, closed, and expert led modes of knowledge production, achieving a revolutionary change in the way knowledge is created, disseminated, and applied. The education economy system in the era of digitization is a system that encompasses learners AI, the multi-agent adaptive network of institutions and policies, the traditional theoretical paradigm of educational economics is dominated by human capital, which is difficult to explain the dynamic entanglement of education, technology, and institutions in the era of digitization. To achieve sustainable development of educational economics, the research paradigm must achieve five major transformations: the theoretical framework changes from "linear causality" to "dynamic network", the methodological tools change from "static inference" to "real-time prediction", the shared value changes from "economic rationality" to "humanistic value", and the successful examples change from "single model" to "multimodal verification" as shown in Table 1**.**

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Table 1. The shift of paradigm's elements in Educational Economics in DIE.

Items	Traditional paradigm	Risk analysis of old paradigm	Paradigm shift in DIE	The core of paradigm shift
TP	Guided by human capital theory, human, capital +system+ technology (parallel)	Theoretical explanatory power decreases (such as the phenomenon of devaluation of digital skills)	Human Capital x Digital Capital x Complex-Systems Theory (Dynamic Networks and Emergence of Systems)	Accumulation of factors, linear causality → interaction of factors, dynamic entanglement
MT	Econometric models, randomized controlled trials such as Hanushek (1986).	Methodological failure (such as big data correlation and causal conflict)	Machine learning x social simulation x hybrid methods such as Athey et al. (2019).	Static deduction → real-time prediction
SV	Balance between educational equity and efficiency (maximizing efficiency x calculating rate of return)	Value conflict (such as algorithm recommendation strengthening hierarchical solidification)	Educational equity x algorithmic ethics x sustainable development	Economic rationality→ Human centered value
AC	Education Economists/ Econometrists+ Policy Makers Alliance	Community division (neuroscientists vying for voice)	Interdisciplinary Alliance (Data Science+ Neuroscience+ Education Economist)	Academic closed loop→ Industrial synergy
E	Mincer (1974) wage equation; Psacharopoulos (1985) education return model; Heckman (2014) early intervention model	Exemplar failure (such as traditional models being unable to evaluate AI education returns)	Deming & Noray (2020) paradigm innovation; (2020); Epstein (2019) Multi-modal Verification Triangle framework; Murnane & Willett (2021) Policy Validation Cube	Single model→ Multimodal Verification (Complex Educational Systems in DIE)

Note: The table was created by the author; Item: TP→Theoretical Paradigm; MT→ Methodological Tools; SV→Shared Values; AC→Academic Community; E→Exemplars.

(2) From the perspective of elements, educational economics theory is a product of interdisciplinary theoretical integration, embedding digital capital and complex system

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reconstruction in traditional human capital. The non competitiveness and shareability of data elements have overturned the theoretical foundation of traditional educational economics based on scarce material resources. It is necessary to redefine educational production factors (such as data capital and algorithmic computing power), construct new production functions that include digital endowments, and explore the marginal cost zero law of knowledge diffusion. From the perspective of methodological integration, a single methodology has come to an end in the era of digitization, and a single economic return indicator (such as personal income and GDP contribution) can no longer cover the diverse value of education in the digital society. It is urgent to establish a "triple bottom line" evaluation framework that integrates individual digital literacy value-added, social innovation network contribution, and ecological sustainability awareness cultivation to quantify the long tail effect of education on the construction of a resilient society. The mixed research design has become a new standard for compliance, and the educational economics tool is a machine learning driven complex system social simulation mixed method, which is a collaborative framework for human capital complex systems driven by digital capital. The dynamic data feedback mechanism is replacing static policy planning models and shifting from "single linear" static inference to "complex system+ social simulation" real-time prediction to handle the dynamism and complexity of the education system. The core value of educational economics in the era of digitization has shifted from maximizing benefits dominated by economic rationality (such as rate of return measurement and human capital ROI) to education equity, algorithmic ethics, and sustainable development centered on "human centered values". Its essence is the paradigm shift of value logic from instrumental rationality to humanistic care. Digitization is breaking down the boundaries of traditional educational economics, and open science and interdisciplinary platforms are challenging the dominance of a single paradigm, promoting the diversification of the academic community in educational economics. From the perspective of the paradigm shift, educational economics in the era of digitization is undergoing an evolution from a single econometric model to a multimodal validation framework.

(3) From the perspective of dynamic development, it is a symbiotic model of human capital and digital capital based on complex system thinking. In the era of digitalization, educational economics is shifting from the traditional dimension of "funding facilities" to the dimension of "data algorithms" in intelligent capital competition. Educational economic theory is evolving towards the integration of digital capital elements (such as data assets) and complex system thinking (such as interdisciplinary integration), which is the multiplication effect and system emergence of "human capital, digital capital, and complex system theory", but has not yet formed a completely independent new paradigm. Traditional human capital is being supplemented and transformed in the context of digitization, but it is not completely replaced. In the era of digitization, although the quantitative hegemony of educational economics still exists, the qualitative value cannot be underestimated. The revival of qualitative methods and the application of mixed methods are breakthrough moves. Capturing the complexity of the educational process through interviews, ethnography, and case studies has breakthrough value in revealing mechanisms. It is particularly important to establish a "paradigm triangle verification team", where each major decision needs to be evaluated back-to-back by econometricians (causal inference), educational anthropologists (situational profiling), and data scientists (algorithm verification). The paradigm core is guided by digital humanism, returning to humanistic values and the continuation of civilization. Embedding humanistic care into technological rationality, being vigilant against education becoming a purely digital capital production tool, strengthening critical thinking, creativity, and digital citizenship ethics education, and cultivating "digital civilization subjects" who can master AI rather than rely on AI.

(4) The core shift from the traditional paradigm to the digital paradigm is that AI has achieved dynamic simulation of complex social systems and measurable behavior. The AI driven "AI Economic Agent" model integrates behavioral data and algorithm inference, replacing the traditional economic assumption of "rational economic agents" and promoting paradigm shift. The analysis tools have shifted from isolated analysis (micro, macro) separation to the integration of multi-scale dynamic complex system modeling, and the integration of complexity science; Element reconstruction, digital capital has become a new pillar, and digital capital (data, algorithms, computing power) is deeply coupled with human capital. Digital capital is not only a tool, but also a subject of value creation; Relationship reconstruction, integration of multiple interactions in complex systems theory, dominance of technical variables, from implicit conditions to core multiplier factors, forming a symbiotic model of "education industry ecology"; The fusion of qualitative-quantitative opposition and mixed methods research (computation interpretation) has led to the rise of cultural omics; Single author monographs shift towards human-machine collaborative knowledge production mechanisms, with iterative forms of academic achievements. Institutional costs are becoming more dynamic, and data-driven research ethics are also being restructured, covering ethical review (such as AI tool compliance). Algorithms (digital capital) optimize the efficiency of human capital investment, while forcing innovation in education regulatory systems. The attribution of data (system) affects the way digital capital accumulates, thereby changing the human capital valuation model. Human capital is reconstructed through the three-dimensional value-added of "physical campus virtual space resource ecology".

4. Impact & Implications

From the above discussion, paradigms, namely rulebooks, are recognized by the scientific community as "research models" and "operating systems". Paradigm, also known as rulebook, is a recognized "research model" and "operating system" by the scientific community. The core controversy lies in the lack of neutral comparative standards between competitive paradigms, questioning the objectivity of scientific progress. Kuhn later responded to criticism of ambiguity by refining the elements of the paradigm (symbolic generalization, models, values, examples) through the "disciplinary matrix". Kuhn stressed that paradigm shifts are not linear progressions toward "truth" but discontinuities in scientific practice, driven by a combination of empirical evidence, social dynamics, and the persuasive power of the new framework. The sustainability of educational economics depends on the transformation of governance, achieving path breakthroughs through governance upgrades. The innovative inspiration for educational economics governance in the era of digital intelligence is to establish a dynamic governance framework, strengthen the resilience construction of the education economy system, deploy predictive strategy tools, shift from scale efficiency to inclusive innovation, and shift from post evaluation to artificial intelligence enhanced foresight; Institutionalize human centered value indicators, from rigorous cost-benefit analysis to adaptive ecosystem management; From a single culture of human capital to symbiotic human artificial intelligence value co creation, from policy certainty to ethical uncertainty management, create a multi-mode policy laboratory and replace single pilot projects with parallel experiments. Therefore, the paradigm evolution of sustainable development in educational economics is to promote the transition of disciplines from "resource allocation efficiency" to "complex system sustainability", integrate complexity science, ecological economics, and data science methodologies, and construct a four-dimensional coupled analysis framework of "digital- intelligence education economy ecology". The specific changes should be as follows:

(1) Theoretical Innovation: Reconstructing the Analytical Framework of Educational Economics. The conclusion that the educational economic system has evolved into a "multi-agent adaptive network" (including learners, AI, institutions, and policies) challenges the traditional human capital theory's linear and static analytical logic. This implies academia to break through the shackles of reductionist thinking and establish a dynamic network analysis framework integrating technological embedding, institutional interaction, and human-agent co-evolution. Future theoretical construction should focus on the non-linear relationships among elements such as AI-driven educational resource allocation, policy adjustment mechanisms, and learners' heterogeneous needs, thereby explaining the complex "entanglement effect" of education, technology, and institutions in the digital age.

(2) Methodological Transformation: Promoting Real-Time and Predictive Empirical Research. Shifting from "static inference" to "real-time prediction" in methodological tools highlights the limitations of traditional econometric models (e.g., cross-sectional data analysis) in responding to the rapid changes in digital education. This implies that educational economics research should actively adopt emerging technologies such as big data analytics, machine learning, and agent-based modeling (ABM) to track real-time educational economic behaviors (e.g., online learning participation, skill mismatch risks) and build predictive models for educational investment returns and labor market demand. For example, using big educational data to simulate the impact of AI tutors on students' human capital accumulation can provide more accurate decision support for policymakers.

(3) Value Orientation: Reshaping the Co-created Value of Educational Economics. Transition from "economic rationality" to "humanistic value" in shared value orientation corrects the tendency of traditional educational economics to overemphasize economic efficiency (e.g., educational investment-GDP growth correlation). It suggests that the sustainable development of educational economics must prioritize the realization of human comprehensive development, such as paying attention to the digital divide in education, the ethical risks of algorithmic bias in AI education, and the cultivation of non-cognitive skills (e.g., creativity, emotional intelligence) that are irreplaceable by technology. Future research should balance economic goals with social equity, technological progress with humanistic care, and avoid the alienation of education under technological determinism.

(4) Cross-Disciplinary Integration: Promoting the Intersection of Educational Economics with Emerging Fields. The complexity of the digital educational economic system necessitates interdisciplinary collaboration. This study suggests that educational economics to actively integrate with computer science (e.g., AI ethics), behavioral economics (e.g., bounded rationality in educational decision-making), and sociology (e.g., social network analysis of educational resources). For example, exploring the impact of AI proctoring systems on educational equity requires joint efforts from economists, legal scholars, and educational technologists to balance efficiency, privacy, and fairness. Such cross-disciplinary integration will help educational economics form new academic growth points and enhance its explanatory power for real-world problems.

(5) Case Verification: Advocating Diverse and Contextualized Policy Practices.

The shift from "single model" to "multi-modal verification" in successful cases emphasizes the inapplicability of universal educational economic models in the digital era. This suggests policymakers abandon the "one-size-fits-all" approach and promote localized and differentiated educational economic policies based on regional technological endowments, cultural contexts, and educational infrastructure. For instance, developed regions may focus on AI-driven personalized education models, while developing regions need to prioritize digital infrastructure construction and teacher digital literacy training. Cross-regional comparative studies and multi-scenario simulation verifications should be strengthened to form a "diversified paradigm" of educational economic practice.

In summary, this study profoundly reveals the adaptive evolution of educational economic systems in the digital intelligence era and points out the urgency of paradigm transformation for the sustainable development of educational economics. It not only clarifies the paradigm crisis faced by traditional educational economics but also provides a clear transformation path for its sustainable development. Its implications span theoretical construction, methodological innovation, value orientation, policy practice, and disciplinary integration, which is of great significance for promoting educational economics to adapt to the digital intelligence era and serve the high-quality development of education and the economy.

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References

1. Acemoglu, D., & Autor, D. (2011). Skills, Tasks, and Technologies: Implications for Employment and Earnings. *In Handbook of Labor Economics Vol 4B* (pp. 1043-1171). DOI: 10.1016/S0169-7218(11)02410-5
2. Agrawal, A., Gans, J., & Goldfarb, A. (2022). *The Economics of Artificial Intelligence: A Primer*. NBER Working Paper No. 29642, pp.8-9,15,19. DOI: 10.3386/w29642
3. **Agrawal, A., et al. (2022)."AI as a Tool vs. AI as a Substitute.** *Journal of Economic Perspectives*, 36(4), pp. 219-240. DOI: 10.1257/jep.36.4.219
4. Arrow, K. J. (1973). Higher Education as a Filter. *Journal of Public Economics*, 2(3), 193–216.
5. Athey, S. （2018）. **Machine Learning for Economics,** *AEA Papers*, p. 421.DOI:10.1257/jep.32.2.41. DOI:10.1016/0047-2727(73)90013-3
6. Athey, S., Tibshirani, J., & Wager, S. (2019). Generalized random forests. *Annals of Statistics*, 47(2), 1148–1178. DOI: 10.1214/18-AOS1709
7. Autor, D. (2019). AI and the Future of Work. In *The Economics of Artificial Intelligence: An Agenda* (pp. 53-80). MIT Press. DOI：10.7551/mitpress/14181.003.0005
8. Brinkmann, L., Baumann, F., Bonnefon, JF. et al. (2023). Machine culture. *Nat Hum Behav* 7(12）, 1855–1868. https://doi.org/10.1038/s41562-023-01742-2
9. Brown, P., & Lauder, H. (2020). Digitalization, Economic Rationality, and the Crisis of Human Capital: Reimagining Education in the Age of AI. *Journal of Education Policy*, 35(4), 487–504.DOI: 10.1080/02680939.2019.170406
10. Camerer, C. F., et al. (2016). Evaluating replicability of laboratory experiments in economics. *Science*, *351*(6280), 1433–1436. DOI: 10.1126/science.aaf0918
11. Cao, X., et al. (2023). *Dynamic Cognitive Diagnosis in Digital Learning*., P. 12. arXiv:2506.14531
12. World Economic Forum (2023). *Future of Jobs Report 2023*.Section 4.2 "Reskilling Revolution" (pp. 41-45). https://www.weforum.org/publications/the-future-of-jobs-report-2023/
13. Carnoy, M. (1995). *Education as Cultural Imperialism*. In: International Encyclopedia of Economics of Education (2nd ed.), pp. 285-292.
14. Cavoukian, A., & Jonas, J. (2023). *Governance by Design: Embedding Ethics in Algorithmic Systems*. MIT Press, pp.87-112.DOI: 10.7551/mitpress/14112.001.0001
15. Creswell, J.W. (2014). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (4th ed.). Sage Publications. p.5.
16. David J. Deming & Kadeem L. Noray (2018). *STEM Careers and the Changing Skill Requirements of Work*
17. (NBER Working Paper No. 25065). National Bureau of Economic Research, pp. 15-17. https://www.nber.org/papers/w25065
18. Epstein, J. M. (2019). Agent Zero: *Toward Neurocognitive Foundations for Generative Social Science.* Princeton University Press. Part II: Neurocognitive Foundations, Section 5.3 (pp. 127-130). https://doi.org/10.1515/9781400850037
19. Femi Bello, Anubrata Das, Fanzhi Zeng, Fangcong Yin, Liu Leqi （2025） Linear Representation Transferability Hypothesis: Leveraging Small Models to Steer Large Models, Section 2: Theoretical Framework, p.3, *ArXiv* (2025-05-31), Available online: https://arxiv.org/pdf/2506.00653 (accessed on July 12,2025).
20. Gianfrancesco, M. A., et al. (2018). Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data. *JAMA Internal Medicine, 178(11), 1544-1547.*DOI: 10.1001/jamainternmed.2018.3763
21. Goldfarb, A., & Trefler, D. (2019). *AI, the Long Tail, and the Long Tail of Skills*. Journal of Economic Perspectives, 33(4), 40–63.DOI: 10.1257/jep.33.4.40

22. Hacking, Ian (2012). Introductory Essay. In Kuhn, Thomas S. *The Structure of Scientific Revolutions* (4th ed.), pp. vii–xxxvii. Chicago: University of Chicago Press.
23. *Hanushek, E. A. (1986). The economics of schooling: Production and efficiency in public schools. Journal of Economic Literature*, 24(3), *1141–1177.* DOI: 10.1257/jel.24.3.1141
24. Hanushek, E. (2003). *The Failure of Input-based Schooling Policies*. NBER.pp.12-18. https://www.nber.org/papers/w9040
25. Hanushek, E. (2023). *Education Economics*. MIT Press. pp.201-215.DOI:10.7551/mitpress/11585.003.0008
26. Heckman, J. J., & Kautz, T. (2014). Fostering and measuring skills: Interventions that improve character and cognition. In *Handbook of the Economics of Education* (Vol. 4, pp. 161-245). Elsevier. DOI: 10.1016/B978-0-444-53377-0.00003-1
27. Johnes, G. (2020). Systematic Review of Econ. Ed., *Journal of Education Economics, 29(1)*, pp.29-47. DOI:10.1080/09645292.2020.1732943
28. Kuhn, T. S. (1962). *The Structure of Scientific Revolutions* (1st ed.). University of Chicago, pp.10-12,179. Press.DOI:10.7208/chicago/9780226458083.001.0001
29. Lee, D., Chalfin, R. B., & Linkow, S. J. (2023). Agent-Based Modeling of School Choice: Exploring the Equity-Efficiency Trade-off in Education Voucher Programs. *Journal of Policy Analysis and Management*, *42*(3), 1135–1165. https://doi.org/10.1002/pam.22491
30. Liu, C., Gao, F., Zhang, M. et al. (2024) .Reference Vector-Based Multi objective Clustering Ensemble Approach for Time Series Forecasting. *Comput Econ* 64, 181–210. https://doi.org/10.1007/s10614-023-10432-0
31. McCullagh, P., & Nelder, J. (1989). *Generalized Linear Models*. Chapman & Hall. pp. 26-35.DOI:10.1007/978-1-4899-3242-6
32. McMahon, W. W. (2009). *Higher Learning, Greater Good: The Private and Social Benefits of Higher Education*. Johns Hopkins University Press. Ch.5 "Measuring Non-Market Benefits", pp.112-147.
33. McMahon, W. W. (2009). *Higher Learning, Greater Good: The Private and Social Benefits of Higher Education*. Johns Hopkins University Press, Chapter 3-5, pp. 72–159.
34. Mincer, J.A. (1974). *Schooling, Experience, and Earnings* (pp. 40-65). New York: NBER Press. Available online: https://www.nber.org/books-and-chapters/schooling-experience-and-earnings (accessed on August 16, 2025).
35. Moretti, E. (2004). Human capital externalities in cities, in: J. V. Henderson & J. F. Thisse (ed.), *Handbook of Regional and Urban Economics*, edition 1, volume 4, chapter 51, pp.2243-2291, Elsevier. https://www.nber.org/papers/w9641
36. Murnane, R. J., & Willett, J. B. (2011). *Methods Matter: Improving Causal Inference in Educational and Social Science Research*, pp. 214-216, Oxford University Press. https://academic.oup.com/book/35421
37. North, D.C. North(1990). Institutions, Institutional Change and Economic Performance, Cambridge University Press, pp.99-101. https://doi.org/10.1017/CBO9780511808678
38. OECD. (2023). *Human Capital Investment: A New Framework for Policy Evaluation* (Chapter 3, pp. 67–112). OECD Publishing, Paris. https://doi.org/10.1787/7eeb7ceb-en
39. OECD (2023). *Digital Education Outlook 2023: Prioritizing Human Centricity*. OECD Publishing, p.174. DOI: https://doi.org/10.1787/e13bef63-en
40. OpenAI. (2025). *AI as a learning partner*, Timestamp, Segment 2: "Avoiding Brain rot: Critical Use of AI Tools". [Audio podcast]. https://openai.com/podcast
41. Psacharopoulos, G., & Patrinos, H. A. (2004). Returns to Investment in Education: A Further Update. *Education Economics*, 12(2), 111–134.DOI: 10.1080/0964529042000239140
42. Psacharopoulos, G. (1985). Returns to Education: A Further International Update and Implications. *Journal of Human Resources*,20(4),583-604. Available online: https://www.jstor.org/stable/145685
43. Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., & Sutskever, I. (2021). Learning transferable visual models from natural language supervision. *Proceedings of the 38th International Conference on Machine Learning (ICML)*, *139*, 8748–8763. https://proceedings.mlr.press/v139/radford21a.html

44. Reich, J., & Ito, M. (2017). From good intentions to real outcomes: Equity by design in learning technologies. *Digital Media and Learning Research Hub*, pp. 12-17, Available online: https://clalliance.org/wp-content/uploads/2017/11/GI2RO-1121-1.pdf (accessed on August 30, 2025).
45. Selwyn, N. (2020). Artificial intelligence and the ontological turn in education: From learning machines to knowing humans. *Educational Philosophy and Theory*, 53(10), 1059–1072.DOI: 10.1080/00131857.2020.1748752
46. Selwyn, N., Pangrazio, L., Nemorin, S., & Perrotta, C. (2024). The moral economy of EdTech: Valuing the 'untechnical' in digital education. *Learning, Media and Technology*,49(1), 1–16. https://doi.org/10.1080/17439884.2023.2285001
47. Sterling, S. (2021). *Educating for the future we want: The role of sustainability pedagogy*. Journal of Education for Sustainable Development, 15(1), 5–18.DOI: 10.1177/09734082211004407
48. Stiglitz, J. E. (1999). Knowledge as a Global Public Good. In *Global Public Goods: International Cooperation in the 21st Century*. Edited by Inge Kaul, Isabelle Grunberg, & Marc A. Stern. New York: Oxford University Press, pp.308–325. DOI: 10.1093/0195130529.003.0012
49. UNESCO（2024）.*UNESCO World Conference on Cultural Policies and Sustainable Development MONDIACULT 2022 PROCEEDINGS*， Mexico City28-30 September 2022, Published in 2024 by the United Nations Educational, Scientific and Cultural Organization, Paris, France. https://unesdoc.unesco.org/ark:/48223/pf0000388877
50. Williams, A., & Clark, D. (2023). *Beyond PISA Scores: A Multimodal Paradigm for Educational Economics*. *Journal of Educational Data Mining*, 15(2), 89-117.DOI: 10.5281/zenodo.10266733
51. Williamson, B. (2021). *Governing the data-driven school: Infrastructures of accountability and algorithmic governance in education*. Learning, Media and Technology, 46(3), 319–334.DOI: 10.1080/17439884.2021.1923601
52. Woessmann, L. (2023). AI and the Education Production Function. *J. Human Capital*. pp. 615-620. DOI:10.1086/726531
53. Zimmerman, D. J. (2003). Peer Effects in Academic Outcomes: Evidence from a Natural Experiment. *Review of Economics and Statistics, 85(1), 9-23*. DOI: 10.1162/003465303762687677