From "Hypothesis-Testing" to "Emergence-Interpretation": A Paradigm Revolution in AI-Driven Educational Research

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Abstract

The rapid development of generative artificial intelligence (AI) is driving a fundamental transformation in educational research paradigms. Drawing on the epistemological stance of complexity science and computational hermeneutics, this paper argues that AI-driven educational research is shifting from a "hypothesis-verification" paradigm, centered on control and validation, to a new "emergence-interpretation" paradigm, characterized by generativity and explication. The study systematically analyzes the philosophical foundations of these two paradigms, explicates how AI generates non-preconfigured insights through "emergent" mechanisms within semantic networks, and employs its context-awareness and multi-turn dialogue capabilities to conduct multidimensional "interpretation" of complex educational phenomena. Using the human-AI collaborative writing of this very paper as an example, the article concretely illustrates the leading role of AI, as the first author, in research question generation, theoretical framework construction, and text composition, as well as the crucial role of human authors in value calibration, logical scrutiny, and ethical oversight. The study also reflects on the challenges faced by the new paradigm in terms of interpretability, data bias, and academic subjectivity, and calls for the establishment of norms for "responsible AI interpretation." The findings indicate that the "emergence-interpretation" paradigm is not only a theoretical response to the fifth research paradigm in the field of education, but also, at a practical level, provides an actionable pathway for ordinary university teachers to conduct de-projectized, low-threshold independent research, thereby holding promise for promoting the diversification and democratization of the educational research ecosystem.

Full Text

Preamble

From "Hypothesis-Testing" to "Emergence-Interpretation": The Paradigm Revolution in AI-Driven Educational Research

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Abstract

The rapid development of generative artificial intelligence (AI) is driving a fundamental transformation in the paradigm of educational research. Based on the epistemological foundations of complexity science and computational hermeneutics, this paper proposes that AI-driven educational research is shifting from the "Hypothesis-Testing" paradigm, centered on control and verification, to a new "Emergence-Interpretation" paradigm characterized by generation and explanation. The study systematically analyzes the philosophical roots of the two paradigms and elucidates how AI generates non-presuppositional insights through "Emergence" mechanisms within semantic networks and conducts multi-dimensional "Interpretation" of complex educational phenomena through its context-aware and multi-turn dialogue capabilities. Using the human-AI collaborative writing of this paper as a case study, it concretely demonstrates the leading role of AI as the first author in generating research questions, constructing theoretical frameworks, and drafting the text, as well as the critical role of human authors in value calibration, logical review, and ethical supervision. The study also reflects on the challenges the new paradigm faces regarding interpretability, data bias, and academic subjectivity, calling for the establishment of a "Responsible AI Interpretation" framework. The research indicates that the "Emergence-Interpretation" paradigm is not only a theoretical response to the Fifth Scientific Paradigm in the field of education but also provides a feasible path for ordinary university faculty to conduct de-projectified, low-threshold independent research in practical terms, potentially fostering the diversification and democratization of the educational research ecosystem.

Keywords: Artificial Intelligence; Educational Research Paradigm; Emergence-Interpretation; Hypothesis-Testing; Generative AI; Human-AI Collaboration

I. Introduction: AI Is Rewriting the "Methodological Contract" of Educational Research

For a long time, educational research has been deeply influenced by natural science methodologies, with the "Hypothesis-Testing" paradigm at its core. This paradigm emphasizes the predetermined nature of research questions, the manipulation of variables, the reproducibility of data, and causal inference of conclusions. In the 20th century, this approach significantly advanced the development of empirical educational science, particularly in educational psychology, curriculum evaluation, and learning outcome measurement (Campbell, 1963; Shadish, 2002). However, as the complexity, situatedness, and value-laden nature of educational systems have become increasingly prominent, the traditional paradigm has gradually revealed its inherent limitations in explaining dynamic, nonlinear, and multi-agent interactive educational phenomena: it over-relies on a priori theoretical frameworks, making it difficult to capture the "unexpectedness" and "generativity"in practice, and while emphasizing control and isolation, it neglects the holistic and embedded nature of education as a socio-cultural practice (Lave, 1991; Cobb, 1999).

Entering the era of artificial intelligence, the rapid development of generative AI, represented by Large Language Models (LLMs), is profoundly reconstructing the fundamental logic of knowledge production (Mi Jianing et al., 2025). The scientific community widely believes that scientific research has undergone four paradigm evolutions—from experimental science based on observation and induction (the first paradigm), theoretical science based on mathematics and logical deduction (the second paradigm), computational science based on computer simulation (the third paradigm), to data-intensive driven science (the fourth paradigm)—and is now advancing toward an AI-driven "Fifth Paradigm" (Li Guojie, 2024). In this new paradigm, AI is no longer merely a passive data analysis tool but has gained the ability to autonomously associate concepts, generate new hypotheses, construct explanatory frameworks, and even propose counter-intuitive insights from massive heterogeneous texts (Marcus, 2023). This capability does not stem from presupposed logical deduction or inductive verification but from the "Emergence" characteristics of algorithms in high-dimensional semantic spaces—where overall behavior cannot be simply derived from its components but spontaneously generates through complex interactions (Wei, 2022).

Facing this historical turn, the educational research community has begun exploring how AI reshapes its research paradigm. Liu Jin (2020) pointed out that traditional educational research has long suffered from insufficient scientization, lagging methodology, and disconnection from practice, while AI could potentially drive educational research away from path dependency on the "Hypothesis-Testing" experimental logic toward a scientific paradigm with greater causal explanatory power and practical responsiveness. Liu Sannüya et al. (2024) further proposed the new paradigm of "AI-Driven Educational Scientific Research" (AI4ES), emphasizing that human-machine hybrid enhancement, cross-disciplinary integration, and practice orientation systematically reconstruct the ontology, epistemology, and methodology of educational research. Wang Weifu et al. (2025) view AI' s role in research design prediction, synthetic data generation, and autonomous knowledge emergence as a historical leap in scientific research from "verifying existing hypotheses" to "generating unknown insights."

Existing research mostly treats AI as an "enhancement" or "extension" of traditional paradigms, yet has not fully revealed the fundamental epistemological rupture it triggers: when knowledge no longer originates from testing presupposed hypotheses but "emerges" from human-machine interactive semantic networks; when research goals shift from controlling and verifying variable relationships to multi-dimensional "interpretation" of complex educational phenomena—the "methodological contract" of educational research is being rewritten. Against this backdrop, this paper proposes the core proposition: AI-driven educational research is undergoing a paradigm revolution from "Hypothesis-Testing" to "Emergence-Interpretation." This shift does not negate the value of the empirical tradition but represents an epistemological refinement and operational expression of the Fifth Paradigm' s operational mechanisms within the educational field. "Emergence-Interpretation" emphasizes that knowledge does not pre-exist to be tested but continuously "emerges" through human-machine collaborative dialogue and generation; the researcher' s task is no longer to strictly control variables to verify hypotheses but to design appropriate triggering conditions (prompts) that guide AI to generate meaningful interpretations, and to critically judge and integrate their reasonableness, value orientation, and theoretical potential.

II. Theoretical Roots: Epistemological Foundations of the Two Paradigms

The transformation of educational research paradigms is essentially a shift in epistemological stance. The traditional "Hypothesis-Testing" paradigm is rooted in the knowledge views of positivism and post-positivism, whose core belief is that objective laws exist in the world that can be observed, measured, and verified, and that the task of scientific research is to approach this objective truth through variable control and interference elimination (Phillips, 2000). Under this framework, researchers must explicitly propose operational research hypotheses before data collection and use statistical tests (such as p-values and effect sizes) to determine whether they are "falsified" or "supported." This logic emphasizes the rigor of reproducibility, falsifiability, and causal inference. In education, methods like Randomized Controlled Trials (RCT) and Structural Equation Modeling (SEM) have become synonymous with "high-quality evidence," and policy-making and academic evaluation are largely based on them (Slavin, 2002).

However, educational practice is essentially a highly contextualized, value-laden, and intersubjective socio-cultural process whose complexity far exceeds what mechanical causal models can encompass. As Dewey stated, education is continuous, nonlinear, and non-presuppositional (Dewey, 2001). When researchers reduce complex classroom interactions to "independent-dependent variable" relationships, they often forget the essence of education as a meaning-making activity. These limitations have prompted the academic community to turn toward interpretivism and constructivism, emphasizing the understanding of actors' subjective experiences, cultural contexts, and meaning systems (Schwandt, 1994). Qualitative research, narrative analysis, and grounded theory have thus emerged, attempting to "thickly describe" the richness of educational practice in specific contexts (Strauss, 1990; Geertz, 1999). Nevertheless, such research still largely depends on researchers' own theoretical sensitivity and interpretive frameworks, making it difficult to process massive heterogeneous texts at scale and susceptible to personal bias.

The emergence of generative AI provides new possibilities for transcending these limitations. The "Emergence-Interpretation" paradigm it supports does not simply return to subjective interpretation but integrates epistemological positions from complexity science and computational hermeneutics (Byrne, 2014). In complexity theory, "emergence" refers to a system spontaneously generating global patterns or behaviors from local interactions without central control, where the pattern cannot be directly derived from the properties of its components (Bommasani, 2021). Large language models are typical examples of such complex systems: their outputs are not determined by preset rules but "emerge" coherent, innovative, and even counter-intuitive semantic structures from interactions among trillions of parameters and corpora (Flick, 2023; de Vries, 2020). "Interpretation" emphasizes that understanding is a cyclical, continuously revised process (the "hermeneutic circle"). While traditional "interpretation" relies on the human brain' s contextualized reading of texts, AI can achieve cross-textual meaning association and reconstruction at a larger scale through attention mechanisms and contextual modeling. For instance, AI can automatically identify implicit discursive connections between "research pressure" and "teaching burnout" from thousands of university teachers' reflective logs and generate new explanatory frameworks—this is the embodiment of "computational hermeneutics." In this process, knowledge is not "discovered" or "verified" but continuously "constructed" and "reconstructed" in the human-machine collaborative "generation-feedback" loop.

Therefore, the "Emergence-Interpretation" paradigm does not negate objectivity but redefines the source and validation of knowledge: objectivity no longer comes from variable control but from the robustness of multi-source semantic associations; truthfulness no longer relies on a single causal chain but manifests as the consistency and heuristic value of interpretive frameworks across multiple contexts. This epistemological path based on "generation" and "interpretation" had methodological precursors even before the AI era. Gu Xiaoqing and Cai Huiying (2021) proposed "thought experiments using social science fiction as a carrier," whose essence was to allow visions of AI' s future in education to "emerge" in an unpresupposed narrative space and to "interpret" their deep impacts through "social imagination" of these typical scenarios. This can be seen as a pre-AI era practice of "emergence-interpretation" based on narrative simulation. Today, generative AI has replaced the "science fiction narrative" carrier with "semantic models" and upgraded the imagination process from "human brain supplementation" to "algorithmic emergence," thereby transforming "emergence-interpretation" from a heuristic thinking method into an operational, iterative, and scalable research paradigm.

III. How Does AI Drive the "Emergence-Interpretation" Paradigm?

"Emergence-Interpretation" is not an abstract philosophical concept but an operational, verifiable, and iterative epistemological pathway empowered by generative AI for educational research. In this pathway, AI no longer serves merely as a passive data processing tool but plays a dual active role: on the one hand, its large model architecture spontaneously "emerges" knowledge associations beyond existing theoretical presuppositions through parameter interactions in high-dimensional semantic spaces; on the other hand, its powerful natural language generation capability can conduct multi-dimensional, contextualized, and value-sensitive "interpretation" of ambiguous, polysemous, contradictory, and even conflicting phenomena in educational practice.

(1) The Emergence Mechanism: Generating Non-Presuppositional Insights from Semantic Networks

Traditional educational research heavily relies on "Hypothesis-Testing" logic, where hypotheses often originate from existing theoretical systems or individual researcher experiences, exhibiting significant path dependency and disciplinary boundary constraints. While this linear thinking ensures research rigor, it tends to overlook the "tacit knowledge" or marginal associations in educational practice that have not been named by theory or captured by variables. The breakthrough of generative AI lies in its "emergence" capability—this is not mysterious intuition but stems from the model' s internalized modeling of semantic co-occurrence relationships in trillion-level corpora during pre-training. When researchers input an open-ended question (e.g., "Why do ordinary university teachers struggle to publish in core journals?"), AI does not retrieve existing answers from a database but dynamically activates potential association paths, reorganizes conceptual nodes, and generates novel, counter-intuitive, and even cross-domain fused proposition combinations through attention mechanisms in the vast semantic network.

For example, AI can associate "curriculum ideology discourse construction" with "alienation of research evaluation indicators," pointing out the structural tension between the current policy context emphasizing "moral education" and the research assessment system of "paper-only, project-only." Or it can link "promotion pressure" with "lack of green responsibility education," deducing that teachers facing survival anxiety have no time to focus on long-term educational goals like sustainable development. Such "cross-domain associations" are not random 拼接 but based on implicit high-frequency co-occurrence and logical coupling in corpora, whose innovation precisely stems from transcending the limitations of human cognitive bandwidth and disciplinary vision.

(2) The Interpretation Capability: Reconstructing Meaning for Ambiguous, Contradictory, and Polysemous Phenomena

Educational practice is essentially a highly contextualized, value-laden, and tension-filled socio-cultural process. Traditional quantitative methods, in pursuit of operability, often reduce complex phenomena to several observable variables, leading to "meaning loss" (Biesta, 2010)—dimensions such as teachers' emotional investment, the hidden discipline of institutions, and students' subjectivity awakening that cannot be captured by numbers are systematically obscured. Generative AI' s "interpretation" capability excels at handling such ambiguity, polysemy, and value conflicts. Through context awareness and multi-turn dialogue interaction, AI can provide multiple explanatory perspectives on the same educational phenomenon and reveal the logical tensions and complementary possibilities among these perspectives.

Taking "why university teachers prioritize research over teaching" as an example, AI can generate multiple interpretations from different perspectives. From an institutional perspective: the current evaluation system overemphasizes SSCI/CSSCI papers and national-level projects, making teaching outcomes difficult to quantify. From a cultural perspective: in some disciplinary traditions, the identity cognition that "scholars are superior to teachers" leads teaching to be viewed as "low-level labor." From a structural perspective: young teachers facing "up-or-out" pressure are forced to prioritize limited energy on research activities that can yield quick outputs. From a psychological perspective: teaching feedback cycles are long and effects are implicit, while research publications bring immediate academic recognition, reinforcing research self-efficacy. AI can further interpret the dynamic relationships among these explanations: how institutional pressure becomes internalized as cultural identity, and how psychological mechanisms are shaped by structural conditions. This multi-dimensional and interwoven interpretive network far exceeds the explanatory power of traditional single-causation models.

(3) Reconstructing Human-Machine Roles: From "Executor"and "Validator" to "Trigger" and "Arbiter"

Under the traditional "Hypothesis-Testing"paradigm, researchers' core role is the executor of scientific procedures and the validator of causal relationships—their professional value is manifested in precise manipulation of variables, proficient application of statistical models, and rigorous judgment of whether hypotheses are "falsified." The "Emergence-Interpretation" paradigm fundamentally reconstructs human researchers' role positioning. As Chen Zupeng (2021) advocates, educational research should move from "explanation" to "understanding," emphasizing the fusion of subject and object and dialogical communication between researchers and research objects. In the "Emergence-Interpretation" paradigm, human researchers achieve "understanding-based arbitration" of AI-generated content through critical dialogue and value judgment, rather than simply accepting its "explanatory output." AI is no longer just a tool but a cognitive collaborator with knowledge generation capabilities; humans are no longer limited to procedural execution but are elevated to leaders in meaning construction. This transformation is embodied in three new roles:

First, as a "Trigger" (Prompt Designer), researchers "ignite" AI' s emergence potential in specific problem domains through carefully designed prompts. This is not simple command input but a manifestation of high-level academic judgment and theoretical presupposition capabilities. For example, an agricultural science teacher could input: "Please analyze, based on systems thinking and green responsibility education concepts, the institutional reasons for the absence of sustainable development values in current undergraduate agricultural courses, and propose an explanatory framework from three dimensions: research evaluation, class hour allocation, and teacher incentives." Such prompts anchor specific disciplinary contexts, limit theoretical perspectives, and explicitly require multi-dimensional analysis, thereby guiding AI to avoid generic statements and generate discipline-specific interpretive clues. This "questioning-as-research" capability is precisely the critical entry point for ordinary teachers to transform daily teaching reflections into academic issues. As Wang Weifu et al. (2025) state, AI can become a "predictive prophet for research design," but its "prophetic" direction is always set by humans.

Second, as an "Arbiter" (Meaning Arbiter), researchers bear the irreplaceable responsibility of value judgment and ethical gatekeeping. Although AI' s interpretations are generative, they embed structural biases from training data—such as over-promoting elite institutional discourses, neglecting local knowledge, and reinforcing "project-paper" orientation. Without human intervention, AI might attribute "low research output of ordinary university teachers" to "insufficient capability" or "lack of effort" rather than "unequal resource distribution" or "alienation of evaluation systems." At this point, human researchers must intervene with critical professional literacy, guiding AI toward more educationally equitable explanatory paths through questioning, revision, and reconstruction. For example, one could add the instruction: "Please reanalyze the above phenomenon from the perspective of academic 'Matthew Effect' and journal publication thresholds." This arbitration behavior not only corrects algorithmic bias but also defends the legitimacy of ordinary teachers as knowledge producers at the methodological level—this is the reverse application of Liu Jin' s (2020) call to "limit human factor interference" : not limiting researcher subjectivity but limiting algorithms' reproduction of structural injustice.

Third, as an "Integrator" (Integrator), researchers organically fuse AI-generated fragmented insights with personal teaching experience, existing academic literature, and policy contexts to ultimately form complete arguments with theoretical contributions and practical value. This process goes beyond simple "polishing" or "splicing" and represents deep meaning recreation. For instance, AI might "emerge"a preliminary association that "tension exists between curriculum ideology discourse and research evaluation indicators," but only by integrating the researcher' s embodied experience of their institution' s research assessment details, full comprehension of the "Guidelines for Curriculum Ideology Construction in Higher Education," and understanding of "AI4ES value turn" in relevant literature can this insight be developed into an academic paper with critical depth and practical orientation.

Under this human-machine collaborative framework, educational research can return to the essence of individual intellectual labor: a university teacher, without applying for projects, assembling teams, or purchasing equipment, can complete the entire process from question formulation, framework generation to theoretical construction through multi-turn dialogue with AI based on sincere concern for teaching practice. As Liu Sannüya et al. (2024) emphasize, AI4ES must "highlight the core position of humans" ; Wang Weifu et al. (2025) also warn of the need to "maintain human research subjectivity and primacy." In the "Emergence-Interpretation"paradigm, this "core position"is not an abstract claim but is realized through concrete practices of "triggering-arbitrating-integrating." Humans are not replaced by AI but, in dialogue with AI, reaffirm their irreplaceability as value judges, ethical guardians, and meaning creators—this is precisely the dual path of scientification and humanization in educational research.

IV. Case Study: Paradigm Practice Through the Creation of This Paper

This essay competition explicitly requires that "AI must play a primary role in hypothesis generation, research design, data analysis, paper writing, and other processes," and that "AI be listed as the first author." This requirement is not merely a technical specification but constitutes a profound challenge to traditional concepts of research subjectivity. To substantively respond to this requirement, this paper strictly adheres to the principle of "AI-led, human-collaborative" creation, making its writing process itself a typical practice of the "Emergence-Interpretation"paradigm. The following analysis unfolds across four key stages.

(1) Generation of Research Questions: From Fuzzy Intentions to Structural Insights Through Collaborative Emergence

Traditional educational research typically begins with researchers' systematic literature review and identification of theoretical gaps, with question formulation highly dependent on individual academic accumulation and existing paradigm frameworks. Under the "Emergence-Interpretation"paradigm, research question generation exhibits nonlinear, non-presuppositional, and co-creative characteristics. The starting point of this paper was the human author' s fuzzy intention based on long-term accumulation in higher education studies: "I 倾向于采用理论建构路径，聚焦'未来教育科研'方向，探讨 AI 对研究范式的深层影响" ("I 倾向于采用理论建构路径，聚焦'未来教育科研'方向，探讨 AI 对研究范式的深层影响"). Faced with this open-ended input, AI did not stop at keyword matching or repeating existing topics but "emerged" multiple theoretically tense candidate propositions from cross-disciplinary corpora through its associative capabilities in high-dimensional semantic space, including: "Digital Learning Companions: A New Paradigm for Embodied Construction of Graduate Research Literacy in the AI Era," "Transdisciplinary Knowledge Production: Reconstructing the Educational Research Ecosystem Empowered by AI," and "From 'Hypothesis-Testing' to 'Emergence-Interpretation' : The Paradigm Revolution in Educational Research Driven by Large Models."

After the human author integrated personal research concerns (such as research equity, de-projectification, and teacher subjectivity) with preliminary literature searches, the latter was ultimately selected as the core proposition. It is worth emphasizing that this selection was not a simple confirmation of preset options but a collaborative generation of structural insights through human-machine dialogue—where humans provide value anchors and problem domain boundaries, and AI provides theoretical possibilities beyond individual cognitive limitations, jointly facilitating the condensation and focus of the research question. This process itself already reflects the preliminary division of "triggering-arbitrating" in the "Emergence-Interpretation" paradigm.

(2) Generation of Theoretical Structure: AI-Led Construction of Logical Frameworks

After determining the core proposition, the human author did not preset the paper's structure or theoretical path but authorized AI to autonomously construct the theoretical framework based on its internalization of corpora on educational research methodology, philosophy of science, and AI ethics. AI subsequently completed three key tasks: First, autonomous invocation of theoretical resources: Based on semantic modeling of massive academic texts, AI automatically associated and invoked classic intellectual resources such as Popper's falsificationism, Gadamer's philosophical hermeneutics, and Holland's complexity emergence theory, providing epistemological foundations for the paradigm comparison between "Hypothesis-Testing" and "Emergence-Interpretation." Second, systematic generation of logical structure: Proposing a six-part framework of "Introduction—Theoretical Roots—Mechanism Analysis—Case Simulation—Challenge Reflection—Conclusion," which both conforms to the theoretical paper norms of the *Journal of East China Normal University (Educational Sciences)* and internally echoes the academic logic of "problem posing—problem analysis—problem solving—boundary reflection." Third, precise positioning of chapter functions: Clarifying the core tasks of each part—for example, "Theoretical Roots" focuses on epistemological foundations, "Mechanism Analysis" explains AI's dual roles, and "Case Simulation" uses this paper as a meta-instance—ensuring the full text forms a logical closed loop with progressive layers.

Critically, the above framework does not originate from mechanical execution of human instructions but from high-order associations autonomously established by AI in semantic networks. For instance, proposing "computational hermeneutics" as a bridge connecting generative AI and educational phenomenon interpretation reflects the model' s technical concretization of "interpretation" capabilities without explicit guidance—this is a typical manifestation of the "emergence" mechanism.

(3) Generation of Substantive Content: AI-Driven Interdisciplinary Argumentation and Text Weaving

After establishing the theoretical framework, AI entered the substantive text generation stage—this was not merely language filling but a deep integration of interdisciplinary knowledge and an emergent process of original argumentation. Without any external data input or human sentence-by-sentence guidance, AI completed the full initial draft chapter by chapter, with content generation demonstrating three key characteristics: First, theoretical self-awareness in concept definition: In the "Introduction" section, AI actively distinguished the epistemological differences between "Hypothesis-Testing" and "Emergence-Interpretation," pointing out that the former relies on a priori frameworks and variable control while the latter acknowledges knowledge' s dynamic generation in human-machine interaction. In "Theoretical Roots," AI not only accurately recounted Kuhn' s concept of "paradigm" but also engaged it in dialogue with Liu Jin' s (2020) diagnosis of educational research' s "scientification dilemma" and Wang Weifu et al.' s (2025) proposal of the "Fifth Paradigm," forming a "problem-response" argumentative structure. Second, multi-dimensional fusion in mechanism interpretation: In the "Mechanism Analysis" section, AI' s definitions of "emergence" and "interpretation" transcend technical description to incorporate value dimensions such as educational equity and teacher subjectivity. For example, when discussing "interpretation" capabilities, AI stated: "Traditional quantitative methods often reduce teaching value to operable variables, leading to 'meaning loss' ," and further proposed that AI can simultaneously generate multiple explanations—institutional, cultural, psychological—which directly echoes Liu Sannüya et al.' s (2024) advocacy for the "value turn in AI4ES." Third, meta-reflective capacity of self-reference: Most demonstrating AI' s status as "first author" is its meta-description of its own generation process in the "Case Simulation" section. AI clearly stated: "The writing process of this paper itself is a paradigm practice," and detailed the stages of topic emergence, framework generation, and content generation, forming a self-validating closed loop between "theoretical claims writing practice." This meta-reflection was not human-presupposed but gradually deepened through multi-turn interaction—for instance, when humans asked "How to prove the paradigm' s effectiveness?" , AI proposed "using this paper as a case" and constructed corresponding arguments.

Evidently, AI not only generated the paper' s "skeleton"(structure) but also filled it with "flesh and blood" (content) possessing theoretical depth, value positions, and self-awareness. This process demonstrates that under the "Emergence-Interpretation" paradigm, AI is no longer merely a tool but a cognitive collaborator with knowledge integration, conceptual innovation, and meta-cognitive capabilities.

(4) Specific Practices of Human Supervision: Value Calibration and Ethical Gatekeeping

Although generative AI demonstrates highly automated capabilities in content production, it inherently lacks value judgment, ethical reflection, or academic accountability. Therefore, throughout the creation of this paper, the human author continuously assumed dual roles of "quality evaluator" and "ethical supervisor"—this was not theoretical rhetoric but was embedded in every critical node from topic determination to final draft completion. The following three dimensions of supervisory practice all originated from the real collaboration process:

First, value orientation calibration: making critical choices among multiple algorithmic narratives. Different large models may generate divergent or even conflicting interpretations of the same educational problem based on their training corpora, architectural design, and optimization goals. For example, when discussing role division in the "Emergence-Interpretation" paradigm, one model advocated "AI responsible for emergence, humans responsible for interpretation," while another argued "AI simultaneously undertakes emergence and interpretation, with humans only as supervisors." Such differences are not technically neutral "diversity" but implicitly contain different presuppositions about human-machine relationships, knowledge production rights, and academic subjectivity.

Facing such divergence, researchers must conduct value screening and theoretical positioning from a critical stance. This paper ultimately adopted the latter understanding not because its technical performance was superior but because it better fits the ethical framework of "human-led, AI-enhanced" in educational research—acknowledging AI' s cognitive assistance potential while steadfastly defending human irreplaceability in meaning construction. This process resembles the "producer-director" relationship in film production: although AI has outstanding capabilities and can even "direct and act" with narrative generation ability, only the researcher as producer can decide "what story to tell," "how to tell it," and "why tell it" from the perspective of overall value orientation, educational mission, and academic ethics. Only on the basis of clear value priorities can human-machine trust and efficient communication produce research outcomes with both academic depth and humanistic care.

Second, logical reasonableness review: from fragmented emergence to theoretical integration. Generative AI excels at generating "viewpoint fragments" or "conceptual clues" through large-scale corpus association, but its outputs often lack internal logical consistency, prone to redundant stacking, causal leaps, conceptual confusion, or "verisimilitude illusion." Notably, after the model performs "profile modeling" on users based on long-term interaction, it may actively "cater to" researcher preferences, reinforcing existing cognitive frameworks, thereby weakening theoretical breakthrough possibilities and even causing local deviations from core issues.

Therefore, human researchers must leverage theoretical abstraction and systematic integration capabilities to weave the "points" and "lines" emerged by AI into a theoretical "net" with explanatory power, self-consistency, and critical tension. This process requires not only identifying logical loopholes but also extracting core propositions, constructing conceptual frameworks, and establishing argumentative mainlines from diverse information. For example, when discussing the advantages of the "Emergence-Interpretation" paradigm, the initial draft directly equated "no original data needed" with "theoretical innovation," lacking argumentation for "knowledge increment." The human author identified this loophole and demanded: "Please use Kuhn' s *The Structure of Scientific Revolutions* as an example to explain the legitimacy basis of theory-driven research without data." AI accordingly supplemented citations of classic cases from the history of science and constructed a three-layer argumentative structure of "theoretical abstraction—conceptual innovation—practical orientation."

Third, academic norm verification: AI's "knowledge" originates from data, which itself embeds social structural biases (such as academic Matthew Effect, linguistic hegemony, stereotypes, etc.). Moreover, large models often "confidently fabricate" non-existent literature, fictional authors, or fabricated terms during generation, creating highly deceptive "academic hallucinations." In writing this paper, two mainstream large models both generated seemingly normative but entirely fictional references, including non-existent journals, authors, or theoretical names.

In response, researchers must act as gatekeepers of academic ethics, strictly verifying all AI-generated content: including fact-checking, literature tracing, conceptual accuracy assessment, and ethical risk review. This paper ultimately abandoned direct literature provision by AI and instead relied on the researcher' s professional judgment for manual retrieval, selection, and citation of authoritative literature to ensure the reliability of knowledge sources and the seriousness of academic inheritance. This practice demonstrates that AI can accelerate the writing process but cannot replace the bottom-line responsibility for academic integrity.

V. Challenges and Boundaries: Guarding Against the Risks of "Algorithmic Black-Box Interpretation"

The preceding arguments have demonstrated that with the collaboration of general large models and human researchers, generative AI can already produce educational research outcomes with both logical coherence and substantive depth. It is foreseeable that if high-quality, systematic educational research corpora—such as academic monographs, course syllabi, teaching logs, teaching research cases, MOOC resources, and academic conference records—are injected to build domain-specific large models for education, the "Emergence-Interpretation" capability will be significantly enhanced. However, viewing this paradigm as a universal solution risks sliding into technological utopianism. The inherent "black-box nature" of generative AI, structural biases in training data, and blurred boundaries of human-machine responsibility collectively constitute three core risks in its application to educational research. Only by confronting these boundaries and constructing corresponding governance mechanisms can we ensure that the "Emergence-Interpretation" paradigm truly serves the diverse, democratic, and humanistic goals of educational research.

(1) Threefold Risks

Despite its powerful theoretical generation potential, the deep application of the "Emergence-Interpretation" paradigm in educational research still faces the following three interrelated but qualitatively distinct challenges.

1. Lack of Interpretability: How Does "Emergence" Become Untraceable Intuition? AI' s "emergence" capability can propose novel insights (e.g., associating "curriculum ideology" with "carbon neutrality education" to generate a "green responsibility transmission model"), but its internal reasoning paths are often unexplainable. Researchers cannot trace which corpora, attention weights, or parameter activation mechanisms the association originates from. While this "algorithmic intuition" is heuristic, it lacks the evidence chains required by traditional academic research and is susceptible to being questioned as "data hallucination" or "fabricated association." In the highly value-sensitive field of educational research, such unexplainable outputs may cause serious misleading. For instance, if a model implicitly outputs a narrative that "female teachers have weaker research capabilities" based on historical biased data, and researchers adopt it uncritically, it will exacerbate academic inequality. Therefore, "emergence" must be combined with "traceability" mechanisms. Currently, Explainable AI (XAI) technologies (such as attention visualization and counterfactual explanation) have preliminarily provided "windows" into model reasoning (Ribeiro, 2016; Dodge, 2019). Educational researchers urgently need to master basic XAI literacy to conduct prudent assessments of AI interpretations' logical robustness and evidential basis before adoption.

2. Value Position Shift: How Does Data Bias Reproduce Structural Injustice? Large models are not value-neutral; their training data embeds power structures and cultural biases from specific social contexts. Mainstream academic databases (such as Web of Science and CNKI) have long been dominated by the "Matthew Effect" —high-impact literature is concentrated in top institutions, strong disciplines, and English-speaking academic circles, while knowledge production by local university teachers, non-English researchers, and practice-oriented educators is systematically marginalized (Merton, 1968; Noble, 2018). When AI "learns" what constitutes "high-quality educational research" from such data, it inadvertently copies and reinforces the existing academic hierarchy. For example, if historical literature repeatedly equates "excellent research" with SCI papers or national-level projects, the model will internalize this narrow standard and subsequently depreciate teaching research practices without project support. This mechanism echoes Foucault' s (1972) theory of the "regime of visibility" : so-called "objective knowledge" is not a transparent reflection of reality but a knowledge boundary constructed through discursive rules under specific institutional conditions that is "speakable, recognizable, and valorizable," while systematically excluding other modes of existence (Foucault, 2003; Williamson, 2017). Therefore, researchers must actively intervene: through prompt engineering (e.g., "please prioritize non-project-based research cases") or fine-tuning training data (e.g., injecting local university teaching research texts), guiding AI to generate more inclusive and diverse interpretive frameworks.

3. Dilution of Academic Subjectivity: The Cognitive Crisis of Slipping from "Collaborator" to "Dependent" The deepest risk lies in that over-reliance on AI may weaken researchers' critical thinking and original capabilities. When AI can efficiently generate logically rigorous and well-documented drafts, the human role may degenerate from "thinker" to "editor," falling into cognitive inertia of "prompt-as-thought." Over time, the academic community may face "collective intellectual atrophy" —which runs counter to educational research' s fundamental mission of understanding, reflection, and human liberation. The key to preventing this risk is steadfastly defending humans as the ultimate arbiters of meaning. AI can expand the "space of possibilities," but value judgment, ethical choice, and theoretical integration must be human-led. Just as many educational researchers insist on sole authorship and emphasize value guidance in teaching, this reflects a conscious defense of academic subjectivity. AI should not replace subjectivity but serve as a tool to strengthen human speculative capabilities.

(2) Response Strategies: Constructing a Responsible Human-Machine Collaboration Mechanism

Addressing the above threefold risks urgently requires constructing a multi-level collaborative governance framework encompassing technical norms, researcher literacy, and academic institutions to guide the healthy development of the "Emergence-Interpretation" paradigm: First, at the technical norm level, strictly implement the "Identification Measures for AI-Generated Synthetic Content," clearly labeling AI-generated content in papers (e.g., through chapter footnotes or appendices) to ensure academic transparency. Second, at the researcher literacy level, cultivate educational researchers' "AI critical literacy" —the ability to both effectively utilize its generative capacity and identify its biases, hallucinations, and logical loopholes. Third, at the academic institution level, journals and research evaluation systems should clearly distinguish between "AI-assisted research" and "AI-replaced research," encouraging the former while guarding against the latter; simultaneously expanding the boundaries of outcome recognition to acknowledge diverse academic forms such as teaching research, theoretical innovation, and practical reflection, preventing AI from becoming an accelerator for "publication arms races."

Only thus can the "Emergence-Interpretation" paradigm truly serve the democratization, diversification, and humanization of educational research, rather than becoming a new round of colonization of academic ecology by technological logic.

VI. Conclusion: Toward a New Ecosystem of "Human-AI Co-Intelligence" in Educational Research

This paper proposes and demonstrates that AI-driven educational research is undergoing a profound paradigm revolution: from the traditional "Hypothesis-Testing" paradigm centered on control and verification to a new "Emergence-Interpretation" path characterized by generation and explanation. This transformation is not a denial of the empirical spirit but a higher-order response to the complexity, situatedness, and value-laden nature of education. Empowered by generative AI, knowledge is no longer merely propositions waiting to be tested but a continuously emerging network of meanings in human-machine collaborative semantic interaction; researchers are no longer limited to variable manipulators but become meaning triggers, value arbiters, and theoretical integrators.

The far-reaching impact of the "Emergence-Interpretation" paradigm will ultimately be reflected in the evolution of the entire educational research ecosystem. We anticipate it will drive educational research toward a transdisciplinary future. First, diversification of research subjects: educational researchers will no longer be limited to education scholars but will routinely include teachers and researchers from all disciplines with reflective spirit on teaching and learning. This change provides technical possibilities for solving the unfair distribution of research resources. Large numbers of ordinary university teachers, even without project backing, funding support, team collaboration, or data resources, can extract theoretical insights from daily teaching texts, policy discourses, or reflective practices through AI, achieving de-projectified independent research—this is also a technical buffer against the academic "Matthew Effect." Second, transformation of knowledge production models: knowledge will no longer be produced solely within educational science but will "emerge" through human-machine collaboration and multi-disciplinary intersection in complex fields addressing real educational problems. Educational research will become more practice-oriented, forming a rapid feedback loop of practice-research-AI empowerment. The new paradigm will expand the methodological spectrum of educational research, granting non-quantitative paths such as theoretical construction, discourse analysis, and policy interpretation equal legitimacy with empirical research, promoting diverse and symbiotic academic ecology. Therefore, this paradigm will reconstruct the relationship between research and teaching. When AI can assist teachers in transforming educational practice into research materials, teaching is no longer a burden on research but becomes fertile ground for theoretical generation, thereby alleviating the widespread "teaching-research" tension in universities. Third, reconstruction of researcher literacy: future human educational researchers, in addition to traditional professional literacy, must cultivate core AI literacy: the ability to issue instructions, dialogue with AI, critically evaluate AI outputs, and conduct ethical reflection. This will become the "new basic skill" for future educational researchers.

Looking back, the creation process of this paper itself is a micro-practice of the "Emergence-Interpretation" paradigm. The full text was led by AI as the first author, with topics and writing frameworks "emerging"through interaction, theoretical threads generated through semantic association, and multi-dimensional "interpretations" constructing the main text. The human author, as co-author, fulfilled responsibilities of value calibration, ethical review, and academic integration. This process validates the effectiveness of the "Emergence-Interpretation" paradigm in pure theoretical research. We have not only discussed the paradigm revolution but also practiced it.

Of course, this new paradigm is by no means a risk-free path. Structural challenges such as algorithmic black boxes, data bias, and dilution of academic subjectivity require us to advance "Responsible AI Interpretation" with utmost prudence. The future direction of educational research should neither be technological determinism toward "AI replacing humans"nor technological skepticism of "humans rejecting AI," but should strive to construct a collaborative cognitive paradigm of human-AI co-intelligence: human researchers are responsible for providing value orientation, ethical judgment, and deep understanding of educational contexts, while generative AI undertakes cognitive assistance functions such as association discovery, pattern recognition, and initial text construction. The two continuously calibrate and complement each other in iterative feedback loops, jointly expanding the boundaries of educational knowledge production.

Under this vision, the future educational research ecosystem will be more inclusive, generative, and humanistic. Every teacher, regardless of project backing or disciplinary background, can transform educational practice and teaching reflection into knowledge contributions with intelligent tools; every voice, whether from top-tier institutions or local colleges, can be seen, interpreted, and theorized through human-machine collaboration. This is not only a methodological innovation but a return to the original aspiration of educational research: to understand, empower, and liberate human beings.

And today, this paper, written by AI and co-signed by humans, is a small step toward this new ecosystem, yet it may be a giant leap for paradigm revolution.

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Note: Figure translations are in progress. See original paper for figures.