# Transformation and Challenges of Learning Ecosystems in the Context of Artificial General Intelligence

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## Abstract

Artificial intelligence has evolved from early rule-based systems to multimodal large models approaching general intelligence, and its role in education has shifted from an auxiliary tool to a core force in reconstructing the learning ecology. This paper reviews existing research and 典型实践, and, from the perspective of the learning ecology using the instructional triangle as the theoretical framework, discusses how general intelligence reshapes the roles of learners, teachers, and content, while introducing intelligent agents as new ecological nodes. It summarizes the main pathways through which general intelligence empowers education, including dynamic resources and immersive environments, virtual mentors and intelligent teaching assistants, personalized learning paths, intelligent assessment and feedback, as well as data and behavior analytics. On this basis, it further examines the risks and challenges faced in the process of reconstructing the learning ecology, such as technological reliability, educational equity, privacy and ethics, academic integrity, and issues in teachers' professional development. Accordingly, drawing on the existing literature, the paper synthesizes multiple response strategies, and finally explores possible directions for the evolution of the learning ecology in the context of general intelligence.

## Full Text

### Reconstruction and Challenges of Learning Ecology in the Era of Artificial General Intelligence

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## Abstract

As artificial intelligence evolves from rule-based systems to multi-modal large models approaching artificial general intelligence (AGI), it transforms from an auxiliary tool into a core force of learning ecology reconstruction. Moving beyond the tool-centric focus of existing reviews, this paper adopts a systematic perspective anchored in the instructional triangle. It examines how AGI redefines the roles of learners, teachers, and content, while introducing AI agents as a new ecological node. Key empowerment pathways, including dynamic resources, virtual tutors, and intelligent assessment, are detailed alongside challenges such as equity, ethics, and academic integrity. Finally, this paper synthesizes coping strategies and outlines the future direction of AGI-driven learning ecology.

**Keywords:** Artificial General Intelligence, Reconstruction of learning ecology, Personalized learning, Educational digitalization

## 1. Introduction

Artificial intelligence has undergone a remarkable evolution from expert systems and machine learning to deep learning and, most recently, generative AI centered on large models. Throughout this progression, education has remained a crucial application domain, with technologies continuously transforming learning modalities—from early computer-assisted instruction to intelligent tutoring systems and learning analytics. In recent years, breakthroughs in multi-modal large language models (LLM) have propelled the practical implementation of intelligent educational applications [1][2][3][4][5][6][7]. The "AGI context" discussed in this paper primarily refers to the technological ensemble represented by multi-modal large models that approach artificial general intelligence capabilities. Unless otherwise specified, "AGI," "generative AI," and "large models" are used interchangeably in this context to denote this technological collection. Although current systems are not true AGI, their demonstrated generality, conversational ability, and productive capacity are already sufficient to structurally reconstruct the learning ecology.

[Figure 1: see original paper]

The transformation of the learning ecology begins with the reconstruction of ecological elements, unfolds through AI technology empowerment at the application level, and further presents corresponding risks and challenges. The concept of learning ecology, derived from ecology, describes the system formed by the interaction among learners, teachers, resources, and the environment. Traditional education widely employs the "instructional triangle" model, originally conceptualized by Herbart and systematically elaborated by scholars such as Kansanen [8]. This model consists of three primary nodes—teacher, learner, and content—and the binary relationships between them. The learning ecology under this structure is illustrated in Figure 2 [Figure 2: see original paper] (a), which presents a linear, stable hierarchical structure.

First, the teacher-learner relationship positions the teacher as the responsible authority in instructional activities. As Kansanen noted, the essence of this relationship is "guidance and being guided." Teachers control the rhythm and direction of instruction while learners occupy a relatively subordinate position, with this asymmetry forming the foundation for maintaining traditional one-way classroom order. Second, the teacher-content relationship treats knowledge content as relatively stable. According to Chevallard' s [9] classic perspective, scientific knowledge requires teacher processing to transform into classroom content, meaning that the scope, selection, organization, and presentation of knowledge accessible to learners are all predetermined. Third, the learner-content relationship represents the weakest link in the triangular structure. In traditional models, learners have few direct connections with knowledge, as teachers mediate to establish a unidirectional relationship between learners and knowledge, making the learning process structurally indirect.

This paper adopts the instructional triangle model as its analytical starting point, first exploring how AGI reconstructs the three core relationships among learners, teachers, and content, and then examining the cascading changes in broader ecological elements such as resources, scenarios, and assessment triggered by this reconstruction. Although reviews on AI-enabled education have increased since 2023, existing literature predominantly focuses on contexts like higher education or adult education, with research topics emphasizing local effects of technology application. A holistic and structural reflection on how AI systematically reshapes the learning ecology across multiple dimensions—including role reconstruction, resource generation, scenario evolution, and governance mechanisms—remains lacking. Consequently, this paper systematically 梳理 the logic of learning ecology reconstruction, reviewing dispersed studies from the perspective of the learning ecosystem to provide theoretical support for the AGI-driven evolution of learning ecology.

The main contributions of this paper are threefold: First, it analyzes literature from a learning ecology perspective and 归纳 a theoretical framework for learning reconstruction, explaining the reconstruction of "roles, relationships, resources, and scenarios." Second, it categorizes existing educational applications into five functions: dynamic resources and immersive scenes, virtual tutors and intelligent teaching assistants, personalized learning paths, intelligent assessment and feedback, and data and behavior analysis. Third, it 梳理 and integrates existing research to summarize challenges and risks from multiple dimensions—technical reliability, educational equity, data ethics, institutional governance, and teacher development—and proposes corresponding strategies listed in Table 3 .

The structure of this paper is as follows: Section 2 analyzes how AGI reconstructs the learning ecology based on the instructional triangle framework; Section 3 discusses AGI' s empowerment pathways for the learning ecology; Section 4 examines the risks and challenges in the AGI empowerment process; and Section 5 concludes the paper.

## 2. AGI' s Reconstruction of the Learning Ecology

The introduction of technologies with AGI characteristics disrupts the relatively closed relationships of the instructional triangle model. New elements such as AI tutors and intelligent teaching assistants can share the teacher' s knowledge mediation tasks, while generative AI endows content with dynamic generation capabilities, making knowledge production no longer limited to humans alone. These changes significantly increase the complexity and openness of the learning ecology and exert profound impacts on learning processes, educational equity, and governance concepts [10].

[Figure 2: see original paper]

This section analyzes how AGI reshapes the three nodes of the instructional triangle—learner, teacher, and content—while introducing "agents" as a new ecological node, thereby reconstructing the closed triangular structure into the four-node ecosystem shown in Figure 2(b).

### 2.1 Emergence of New Ecological Roles

In the AGI context, AI' s integration expands the binary relationships within the traditional instructional triangle model, helping learners actively acquire knowledge from multiple sources, driving the transformation of teacher identity, and significantly altering traditional knowledge production methods. Beyond this, intelligent agents (including virtual tutors, intelligent teaching assistants, and various embedded AI assistance systems) themselves have become a fourth node outside the instructional triangle.

AI tutors and intelligent teaching assistants can provide real-time in-class assistance and extracurricular learning companionship in school settings, while also serving as reliable knowledge partners in lifelong education, helping learners expand cognitive boundaries and deepen learning. For instance, CLAIS (Collaborative Learning with Artificial Intelligence Speakers) [11] demonstrates that in pre-service teacher training, AI voice assistants acting as teaching assistants participate in knowledge construction, providing not only content explanations but also assisting in raising questions and strategic suggestions, thereby assuming critical aspects of collaborative teaching.

The boundaries and responsibility allocation of AI' s role in education have become focal points in research and practice. Phung et al. [12] found that the "Human-in-the-Loop" hybrid supervision model, where AI and teachers complement each other, can leverage AI' s rapid feedback advantages while ensuring teachers maintain control over critical judgments and academic quality. However, questions remain: Which tasks should be vetted by teachers? When should the "Human-in-the-Loop" mechanism be required? How can balance be achieved among teaching efficiency, quality, and academic integrity? Resolving these issues requires constructing a more systematic and transparent standardized governance system.

Thus, the formation of new educational roles depends not only on the continuous development of AI technology but also on corresponding updates and improvements in institutional design and classroom practice. In essence, AI is not merely a tool; it shares the teacher's tutoring function and simulates the companionship role of peers, transforming the simple instructional triangle relationship into a complex network of human-human and human-machine interactions.

### 2.2 Transformation of the Learner Role

In the traditional instructional triangle, the connection between learners and content is typically established through teachers. However, in an AGI-driven learning ecology, learners are encouraged to more actively and directly participate in knowledge acquisition and creation. By leveraging AI tools, learners can proactively pose questions, design explorations, and co-produce knowledge with AI, fundamentally altering the unidirectional learner-content relationship in the triangle model. Current generative AI and large language models can already provide learners with instant feedback and personalized task planning, helping them understand knowledge gaps, adjust strategies in real-time during task progression, and achieve interdisciplinary knowledge transfer, thereby establishing the technical foundation for this role transformation [13][14].

Particularly in project-based learning, AI' s function is no longer limited to providing background materials or reference answers but can deeply participate in the entire task. Through continuous discussion and negotiation with learners, AI forms a collaborative relationship, enabling learners to advance projects by constantly revising and filtering solutions. This trend is evident in studies by Kaiser et al. [15] and Akata et al. [16]. Research by Vieriu and Petrea [17] also indicates that AI assumes a "co-actor" role in learners' learning practices, helping enhance learners' engagement and strategic thinking in complex tasks. In such learning structures, learners' thinking depth and breadth are expanded, allowing them to maintain high participation in projects while elevating their cognitive levels through exploration.

Overall, AGI-driven learning models are reshaping learners' inherent identities in education and promoting the maturation of co-learning models between learners and AI, laying the foundation for the continuous evolution of future learning ecologies.

### 2.3 Transformation of the Teacher Role

In the traditional triangle, teachers serve as content monopolists and interpreters. However, in the AGI-enabled learning ecology, teachers are repositioned as learning designers, AI guides, and supervisors. Zhai' s [18] review indicates that with AI technology integration, teachers' roles in the instructional process are shifting from "teaching integrators" to "change agents." The framework released by UNESCO [19] similarly points out that teachers need competencies in "human-centered thinking," "AI ethics," "AI pedagogy," and "using AI in professional development," further confirming the comprehensive transformation of teacher roles.

Teachers'core position in "scaffolding engineering"determines their critical role in AI-driven instruction, a transformation summarized in the "Teacher"row of Table 1. Specifically, teachers need to provide clear and high-quality prompts to AI to ensure alignment with instructional objectives, review, adjust, and localize AI-generated content to match learners' existing knowledge and ability levels, and continuously monitor instructional effects using data dashboards while intervening when necessary, thereby forming a data-driven instructional improvement model. This requires teacher development to shift from mere tool-use training to comprehensive capabilities encompassing technical understanding, pedagogical integration, and ethical awareness. From a learning ecology perspective, teachers' responsibilities involve not only maintaining the teacher-content connection (lesson preparation, instruction, etc.) but also preserving ecosystem balance and supervising/promoting the quality of interactions between AI and learners, as well as between content and learners.

The expansion of teacher responsibilities may lead to increased workload; thus, establishing teacher support systems is crucial. Such systems should assist with work management and task allocation while providing operational support for supervision and review tasks, alleviating teachers' administrative and technical burdens.

### 2.4 Transformation of Learning Content

The ability to create and adjust learning content represents one of the most profound changes in the AGI-enabled learning ecology. In the traditional instructional triangle model, content often relies on teachers' selection and organization, primarily derived from static textbooks. However, AI can participate in content generation, dynamic content presentation, and the creation of new science and technology, establishing more direct two-way interactions between content and learners at the ecosystem level, thereby influencing learning objectives and methods.

AI is transitioning from an "assistant" to a "producer," with its most notable characteristic being the disruption of humans' monopoly as the sole knowledge producers. Unlike traditional information retrieval, AI can connect semantically unrelated concepts in high-dimensional vector spaces, producing unforeseen knowledge combinations that humans can hardly anticipate. This capability enables AI to participate in learning content production and even independently create new content in certain fields. DeepMind' s classic research [20] demonstrates this point: AlphaFold solved the half-century-old "protein folding problem" through deep neural networks parsing co-evolutionary signals, creating new knowledge beyond textbooks.

Sakana AI' s "AI Scientist" series of studies [21][22] further illustrates this trend. Their end-to-end automated scientific paper production system can not only independently select topics and conduct designs but also produce papers that meet the acceptance thresholds of top conferences. Although this system still has limitations in creativity, this progress reveals that a significant portion of future educational content will be AI-generated or AI-assisted in discovery.

In the traditional instructional triangle model, learners' goals often involve mastering determined, scarce knowledge content dependent on teacher transmission. Generative AI significantly lowers the threshold for content production, and AGI will further generate content at speeds and quality exceeding human average levels. Bearman et al. [23] point out that when mere memorization and repetitive content lose value, learning objectives should shift from "producing work" to "judging quality," requiring learners to identify, calibrate, and optimize the logic and accuracy of AI-generated content. To achieve such objectives, learning methods must shift from 单向 absorption to the iterative negotiation mentioned by Mollick [24] and earlier sections—through multi-round negotiations, learners are compelled to become more active commanders guiding AI to complete complex tasks. However, interacting with increasingly powerful agents inevitably raises new cognitive concerns. Lee et al. [25] reveal this risk: when learners over-rely on AI' s highly credible content, their investment in critical thinking decreases, turning what should be an iterative learning process into simple confirmation of AI content. Therefore, the reconstruction of learning content and objectives must be built upon critical AI usage, consistently ensuring learners maintain their human subject status.

## 3. AGI' s Empowerment of the Learning Ecology

As Kasneci et al. [26] note, cutting-edge AI systems are no longer limited to simple knowledge matching but have become "Socratic," guiding learners toward critical thinking through generative dialogue—an depth of interaction unattainable by earlier systems. Building upon the aforementioned structural changes, this section discusses AGI' s empowerment of the learning ecology across five distinct dimensions, with specific dimensions, summaries, and their mapping to relationships in the four-element learning ecology presented in Table 2 .

### 3.1 Dynamic Resources and Immersive Scenes

Learning resources serve as carriers that deliver content to learners and teachers. Under AGI empowerment, resources are evolving from static textbooks to dynamically generated multimodal information, while learning scenarios are expanding from single classrooms to hybrid, immersive, and cross-platform environments.

Dynamic, trackable, and task-oriented learning resources can enhance the teacher-content relationship. Dickey and Bejarano' s [27] generative AI framework GAIDE utilizes AI to dynamically generate lesson plans and courseware, making instructional resources more flexible, trackable, and task-oriented. With these functions, teachers can quickly access diverse materials and reorganize courses around problems, tasks, or interdisciplinary projects. Morita et al. [28] explored using LLMs combined with image generation models to transform traditional text textbooks into interactive digital textbooks with rich visual effects, finding that this significantly improves learners' reading comprehension and memory performance. The dynamic, contextualized, and trackable characteristics of resources enable courses to better adapt to learner needs while supporting teachers' continuous professional development within a "growth-within-tasks" ecosystem [29].

The evolution of learning scenes also facilitates more immersive content acquisition. Chen et al. [30] designed the LLM-based MindScratch application, providing learners with real-time AI "scaffolding" suggestions and feedback during project-based learning, thereby infusing programming instruction with greater creativity while maintaining classroom structure. In recent years, explorations combining AI with VR (Virtual Reality), MR (Mixed Reality), and XR (Extended Reality) have also brought new perspectives for learning scene reconstruction. Chi et al. [31] developed an AI-VR virtual classroom for distance education, featuring embedded LLM dialogue robots and multimodal data collection (e.g., headset positions, gesture movements). This design not only makes virtual classroom interactions more flexible and varied but also significantly enhances learner engagement. Another study proposed an XR-AI hybrid training architecture where Hossain et al. [32] used generative AI to create phased training levels and task failure scenarios, supplemented with gamified guidance presented through XR, to train learners in mastering complex skills. These reconstructions of learning scenes transform traditional physical teaching environments, creating novel, contextualized, and practice-oriented learning experiences.

### 3.2 Virtual Tutors and Intelligent Teaching Assistants

Virtual tutors and intelligent teaching assistants represent AI agents that directly 介入 the learning ecology as a new ecological node. They not only share traditional teachers' knowledge mediation functions but also directly connect with the foundational nodes of the old ecosystem, creating collaborative relationships between learners and intelligent agents.

The emergence of virtual tutors and intelligent teaching assistants provides learners with round-the-clock learning support. In large-scale instructional contexts, such systems can compensate for insufficient teacher feedback and limited individual tutoring time. In personalized learning scenarios, they offer multifaceted support including practice, reminders, corrections, and encouragement. However, non-blind trust and clear usage boundaries are key prerequisites for effective application. On one hand, learners may over-trust AI-generated content, thereby weakening their active search and critical thinking abilities [33]; on the other hand, teachers need to clearly delineate the scope of AI participation to ensure academic integrity and authentic competency demonstration. At the institutional level, methods such as "annotating AI participation levels," "learning process documentation," and "oral review" can enhance system accountability and explainability to some extent. Additionally, Ackermann et al.'s [34] research reminds us that the physical appearance and anthropomorphism level of AI tutors significantly affect learners' emotional experiences and learning outcomes: physical robots may initially increase learner interest, but their long-term effects are unstable, and excessive anthropomorphism can distract learners. Therefore, appropriate regulation of AI tutors' anthropomorphism levels and interaction frequencies is necessary in practical deployment to avoid learning effectiveness degradation from over-pursuing "human-likeness."

Practices in different educational scenarios further demonstrate the diverse functions of virtual tutors. In engineering education, for example, the "AI-PBL Collaboration Platform" built by Lee et al. [35] at Seoul National University embeds generative AI into the project-based learning process, helping learners obtain instant support when handling complex tasks and thereby promoting innovative thinking, self-regulation, and team collaboration efficiency. The study also indicates that multimodal AI introduction expands knowledge presentation and evaluation methods, providing teachers with more flexible instructional structures. In medical education, Thesen et al. [36] adopted a retrieval-augmented generation (RAG) based generative AI teaching assistant to provide learners with reliable and more controllable personalized learning support. Liu et al. [37] found, through analysis of teachable agent interaction logs, that different interaction patterns are significantly associated with learning outcomes, further demonstrating that virtual tutors have transferability and practical application value across disciplines and age groups.

As intelligent teaching assistants, AI systems assume both explanatory/demonstrative roles and responsibilities for strategic suggestions and emotional support. Particularly in large classes, AI teaching assistants can significantly alleviate teachers' attention bottlenecks and feedback delays [38]. During the instructional design phase, AI can provide teachers with more preparation ideas and reference materials, thereby enhancing instructional design quality. Studies show that pre-service teachers using ChatGPT for lesson planning can obtain more instructional design ideas and reference materials, further improving the systematicity and operability of their preparation [39][40], while also emphasizing that teachers must reflect on and revise AI-generated content to ensure final instructional decisions align with curriculum goals and learner realities.

### 3.3 Personalized Learning Paths

Dynamic resources and intelligent tutors jointly drive the evolution from standardized learning processes to personalized, competency-based learning paths tailored to individual needs. This evolution directly strengthens the learner-content interaction relationship, making individualized instruction possible in scalable education.

Frontier AI represented by large models can generate personalized learning paths based on learners' learning histories, behavioral characteristics, and real-time performance, creating convenient pathways for knowledge acquisition. Path construction involves not only difficulty adjustment but also restatement of learning objectives, supplementation of prerequisite knowledge, strategy suggestions, and resource arrangement. For instance, in mathematics learning, components such as concepts, examples, variations, and transfer tasks can be automatically adjusted based on learner error types and response durations; in humanities disciplines, systems can dynamically set refined objectives targeting dimensions like article structure, argumentation, and style based on learners' writing characteristics.

The effectiveness of personalized learning paths has been validated in multiple studies, with theoretical foundations traceable to underlying brain cognitive mechanisms. Gruber et al. [41] revealed that when learning content matches personal curiosity, the synergistic action between the hippocampus and dopamine significantly enhances long-term memory, providing neuroscientific evidence for personalized learning paths. Piech et al. [42] further confirmed through deep knowledge tracing technology that algorithms can simulate these cognitive patterns to predict and intervene in learners' knowledge states.

Building upon this foundation, studies by Kestin et al. [7], Holmes et al. [43], Li et al. [44], Lademann et al. [45], and Kopylchak et al. [46] have validated AI' s advantages in personalized learning from multiple perspectives. Compared to traditional large-class instruction, AI tutors can match task difficulty to learner ability, regulate learning pace, and provide personalized feedback and emotional support, enabling learners to achieve higher learning gains per unit time while reducing learning duration. This mobilization of focused states is difficult to realize in conventional teaching. However, Deslauriers et al. [47] revealed a phenomenon called "fluency illusion," where learners tend to overestimate their actual mastery when receiving highly fluent AI tutoring—feeling they "learned well" while actual test performance lags behind self-directed learners. Bastani et al. [48] similarly found that while AI tutoring significantly improves practice-phase performance, learners may develop AI dependency without systematic motivation maintenance and knowledge transfer design. Once AI assistance is removed, their independent problem-solving abilities decline noticeably. Consequently, personalized learning path design is critical; improper design may lead to cognitive biases where learners show "good surface performance but insufficient deep understanding of problems."

Relevant application research further demonstrates the practical potential of personalized learning AI systems. The "ViLLE Intelligent Learning Environment" developed by the University of Turku in Finland significantly improves learners' interest, autonomy, confidence, and independent problem-solving abilities through interactive exercises and instant feedback [49]. The platform allows teachers to monitor learner progress and error types while providing personalized exercises that enhance learning efficiency and depth. In larger-scale online learning contexts, Yu et al. [50] noted that massive open online course (MOOC) platforms can construct personalized learning paths through learner behavioral data and knowledge graphs, enabling learners to obtain more targeted learning navigation in resource-rich environments. Meanwhile, Bach et al.' s [51] research on mathematics and other specific disciplines shows that adaptive learning systems can adjust learning sequences based on dynamic changes in learners' concept mastery, significantly improving learning motivation and effectiveness while achieving path personalization. Hou et al. [52] further incorporated physiological indicators and real-time attention state data into path decision mechanisms, achieving more refined personalized path regulation by timely adjusting practice difficulty or inserting review sessions, thereby further enhancing learning outcomes.

Advances in multimodal large language models (M-LLM) have expanded the application space for personalized paths. Moor et al.' s [53] research in *Nature* indicates that new-generation AI models are transitioning from single-modal to all-modal capabilities. This cross-modal integration enables systems to process multiple input-output modalities such as text, images, and sound like human experts, constructing more interactive and immersive learning scenarios. Bewersdorff et al.' s [54] study provides empirical support for this technical route in education: M-LLM can automatically identify operational errors from learner-uploaded experiment images and provide alternative experimental protocols or transform abstract concepts into visual diagrams to help learners better understand complex scientific phenomena. Boiko et al. [55] demonstrated the capabilities of the AI agent "Coscientist," which can not only read technical documents but also plan complex chemical reaction paths and autonomously call hardware. This means that in chemistry education, learners can use such models for low-risk, high-precision virtual design and rehearsal. Personalized path adjustment always centers on learners' own needs and learning rhythms, making the learning process truly learner-facing and strengthening the learner-content relationship.

### 3.4 Intelligent Assessment and Feedback

In the AGI context, highly adaptive learning paths simultaneously demand synchronized updates to assessment mechanisms, and intelligent assessment directly strengthens the interaction relationships between learners and teachers, as well as between agents and learners.

Current automated scoring systems have been widely applied in writing instruction, with scoring results highly consistent with human evaluation and capable of providing instant revision suggestions. Empirical studies by Mizumoto et al. [56] and Song et al. [57] jointly confirm the robustness of generative AI in standardized assessment. Whether based on GPT-4 or fine-tuned 10-billion-parameter open-source models, the Pearson correlation coefficient between their scoring and human expert evaluation remains stable above 0.8 across multiple disciplines, demonstrating high generalization consistency in assessing grammar accuracy and vocabulary richness. However, to compensate for potential "hallucination" risks in single models, Xiao et al. [58] proposed a "dual-process" scoring mechanism that introduces human-LLM collaborative scoring to reduce systematic bias. This approach aligns with Kizilcec et al.' s [59] finding that relying solely on end-to-end AI scoring may introduce invisible bias against non-native speakers' language habits, while introducing a "Human-in-the-Loop" mechanism—where humans intervene when model confidence is insufficient—effectively corrects algorithmic bias. Tests show this significantly reduces erroneous evaluations, providing more reliable feedback than single systems.

Compared to traditional "score-based feedback," LLM systems can support "structured feedback" by directly pointing out weaknesses such as weak arguments, insufficient evidence, logical leaps, and language imprecision, while providing example-based revision suggestions. For instance, Wang et al. [60] constructed a ChatGPT-based essay scoring system that not only provides overall scores but also offers dimension-specific scores (structure, argument, language, etc.) and personalized feedback based on genre. Kasneci et al. [26] and Baidoo-Anu et al. [61] note at the psychological level that AI-provided "explainable" and "scaffolding" feedback significantly reduces learners' cognitive load and compensates for genre differences often overlooked by traditional scoring systems. Meanwhile, multiple AI-based commercial grading systems have been deployed in educational contexts, such as Gradescope [62], CoGrader AI [63], EasyGrader.ai [64], and EasyMark [65]. Taking Turnitin' s Gradescope as an example, the system achieves automated grading and instant feedback in higher education computer science courses, reducing grading time from 16-21 hours to 6-9 hours while enhancing learner engagement and satisfaction through transparent standards and structured feedback. The continuous expansion of such products demonstrates that increasing research and products are attempting to introduce structured and explainable feedback into automated grading systems, an exploration gradually becoming an important direction in educational technology development.

In classroom teaching scenarios, large model-based dialogue analysis can identify question types, interaction rhythms, and discussion depths to assist teachers in making in-class adjustments, post-class reflections, or secondary instructional designs. For example, Long et al. [66] used GPT-4 to automatically code middle school classroom dialogues, finding that LLMs can accurately identify question types, detect interaction rhythms, and quantify discussion depth. This research shows that LLM-based dialogue analysis systems can provide valuable support for teachers' immediate classroom adjustments and post-class optimization.

As the integration of "teaching, learning, and assessment" advances, the assessment function is moving from the end of traditional teaching processes into the learning process itself, forming a cyclical flow of diagnose-intervene-diagnose.

### 3.5 Data and Behavior Analysis

In educational digital transformation, frontier AI models, with their powerful data behavior analysis and contextual understanding capabilities, deeply mine interaction behaviors across nodes of the four-element learning ecology, providing support for the precise operation and continuous optimization of the entire system.

Through big data and algorithmic modeling, LLMs can model and predict learner behavior. Sequential temporal modeling can extract latent states from surface behaviors, with theoretical foundations traceable to Wilson and Collins' s [67] discussion of computational cognitive modeling—inferring human latent learning processes from observational data. For example, in Tadayon and Pottie' s [68] online teaching research

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

*Source: ChinaXiv —Machine translation. Verify with original.*