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A Closed-Loop Integration Model of AI Technology in Junior Secondary Mathematics Teaching

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Abstract: The deep integration of digital transformation and artificial intelligence (AI) is driving profound changes in mathematics education. International forums like the 15th International Congress on Mathematical Education (ICME-15) have emphasized "reconstructing teaching paradigms through AI" as a central theme. However, current research often remains limited to a tool-oriented approach involving specific technologies, creating a disconnect between learning and teaching processes. This gap hinders a fundamental solution to the core challenge of balancing standardized education with personalized cultivation. To address this, this study proposes the "AI Dual-Loop Empowerment" model. This data-driven framework establishes a dynamic closed-loop system. Within the "student self-learning loop," activities such as "preview" and "instant diagnosis" generate "learning data." These data, in turn, drive the "teacher teaching loop," where educators perform "learning analytics" and "implement interventions." The outcomes of these interventions feed back into the students' subsequent learning, creating a virtuous cycle in which "learning informs teaching and teaching promotes learning" and enabling continuous "data-driven decision."

Keywords: AI in education; Junior secondary mathematics education; Dual-Loop empowerment model; Digital transformation of education; Scalable personalized instruction; Human-AI collaboration

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1. Introduction

The digital transformation of education is advancing globally, with breakthroughs in technologies such as generative artificial intelligence (AI) driving profound changes in the educational ecosystem [1,2]. This trend is particularly pronounced in mathematics education. China's 2022 Compulsory Education Mathematics Curriculum Standards explicitly emphasize the integration of information technology into mathematics teaching, with a core objective being the use of data to achieve "precision teaching" and "personalized learning" [3]. This vision aligns with international priorities. For instance, the 2024 15th International Congress on Mathematical Education (ICME-15) elevated its focus from "how to use technology" to "how to reconstruct teaching paradigms through AI" [4]. Similarly, the National Council of Teachers of Mathematics (NCTM) underscores that mathematics teachers serve as the bridge connecting students and AI [5].

Despite the promising potential of AI in education, current research and practice face significant limitations:

(1) Tool-oriented tendency and lack of model construction

Existing research often focuses on validating specific AI functions, such as adaptive item banks or automated grading. While studies have confirmed the effectiveness of individual AI tools [6], they fail to elucidate how these tools systematically reshape the teaching structure. Although valuable, these "single-point breakthroughs" lack integration across the entire teaching process—including lesson preparation, instruction, assignments, assessment, and management—and have not yet coalesced into a unified, theoretically coherent instructional model.

(2) Predominance of unidirectional focus and neglect of dual-loop interaction mechanisms

Some studies primarily explore how AI assists teachers' "teaching" [7], paying less attention to students' "learning," and rarely analyzing the data-driven, bidirectional closed-loop interaction mechanism between the two. How does the "student self-learning loop" precisely drive the "teacher teaching loop"? How do teachers' interventions, in turn, optimize the "student self-learning loop"? This data-driven, bidirectional, closed-loop empowerment ecosystem represents a critical blind spot in current research.

(3) Ambiguity in human-AI collaboration and unclear role definition

Although "human-AI collaboration" is a recognized concept [8], discussions on its specific mechanisms and division of responsibilities remain largely conceptual, lacking actionable implementation frameworks. Should AI replace teachers' repetitive tasks or act as an "amplifier" of their pedagogical expertise? How should responsibilities be delineated in classrooms where "AI teachers" and human teachers coexist? How can teachers critically evaluate AI-generated content while infusing it with indispensable emotional support and creative instructional design? These pivotal questions urgently require clarification through the development of a clear model.

To address this gap, this study proposes an innovative "AI Dual-Loop Empowerment" theoretical model. The study first outlines the six theoretical foundations underpinning the model, then elaborates on its core components and operational mechanisms. Finally, it demonstrates the model's theoretical coherence and practical value through a derivation based on a hypothetical junior secondary mathematics teaching scenario.

2. Theoretical foundation

The construction of the "AI Dual-Loop Empowerment" model is well-grounded, drawing deeply from a series of classical and contemporary learning science theories. Collectively, these theories provide a solid foundation for the model's rationality, innovation, and feasibility.

2.1. Cornerstone classical theories

(1) Mastery learning theory

Systematically proposed by the renowned educational psychologist Benjamin Bloom, this theory posits that the vast majority of students can achieve mastery of knowledge and skills, provided they are given sufficient learning time, appropriate instructional conditions, and frequent formative assessment with feedback. The theory emphasizes ensuring students fully grasp fundamental concepts before progressing to subsequent learning. Within the present model, mastery learning theory forms the underlying logic and core objective of realizing the ideal of "large-scale individualized instruction." The "instant diagnosis" within the "student self-learning loop" continuously identifies students' knowledge weaknesses where mastery has not been achieved. The “teacher teaching loop” then leverages this information to conduct “precise instructional design” and “management intervention,” ensuring collective progress for most students. The work of Nye et al., which integrated the AutoTutor and ALEKS systems, demonstrates the effectiveness of continuous diagnosis and personalized support via adaptive technology, providing a practical reference for the “dual-loop” operation of this model [9].

(2) Constructivist learning theory

This theory contends that knowledge is not passively received from teachers but is actively constructed by learners through interaction with their environment, with support from others (including teachers and peers) and necessary learning resources. In this model, constructivism provides the fundamental rationale for how the “dual loops” foster deep learning. The “student self-learning loop” utilizes digital tools like interactive micro-videos and dynamic geometry to create low-threshold, highly interactive virtual exploration environments, effectively stimulating students’ active meaning-making as cognitive agents [10]. Conversely, the “teacher teaching loop,” by organizing group discussions and collaborative problem-solving based on “learning analytics,” places individual preliminary understandings within a learning community for negotiation and refinement, embodying the crucial role of social interaction in knowledge construction [11].

(3) Distributed cognition theory

This theory posits that cognition is not confined solely to an individual’s mind but is distributed across individuals, tools, symbol systems, and the environment that constitute a functional system. In this model it provides the core framework for understanding the essence of “human-AI collaboration.” It reveals that the “student self-learning loop” and the “teacher teaching loop” are not merely functional additions but constitute a dynamic, distributed cognitive system. Research by Guo et al. emphasizes the critical importance of maintaining “human agency” as central in collaborations with AI, noting that a loss of student ownership can diminish their agency [12]. Haraldsrud et al. highlight the importance of students effectively coordinating generative AI as a cognitive partner, distinguishing between “productive” and “unproductive” interaction patterns [13]. This finding serves as both a caution and a guide for designing the “self-learning loop” in this model. Ferrario et al., arguing from a philosophical epistemological standpoint, demonstrate that when humans successfully “appropriate” AI to form a “hybrid cognitive agent,” they can exhibit cognitive capabilities surpassing those of the individual parts, thereby attaining genuine epistemic authority and subsequently achieving an overall leap in teaching efficacy [14]. Together, these studies—from sustaining human agency and optimizing interaction patterns to arguing for the legitimacy of hybrid agents—provide theoretical grounding for the “human-AI collaboration” design in this model, spanning micro to macro levels.

2.2. Contemporary theoretical perspectives

(1) Precision education theory

Precision education is a data-driven paradigm that leverages advanced information technologies, such as artificial intelligence and learning analytics, to comprehensively collect and analyze learning process data, thereby achieving personalized education [15]. The present model represents a concrete instantiation of the precision education paradigm within the classroom teaching context. The success of the “precision education timely intervention system” developed by Lee et al. in K-12 STEM fields provides cross-disciplinary support for the model’s core assumptions [16]. Furthermore, the hybrid deep learning framework constructed by Altaf et al. methodologically illustrates the required technical depth and data breadth for realizing precision education [17]. Precision education theory offers comprehensive support for the "AI Dual-Loop Empowerment" model, from conception to practice. Specifically, the "self-learning loop" enables the data-driven diagnosis essential to precision education, while the "teaching loop" facilitates the personalized, timely interventions that precision education pursues.

(2) Learning analytics and the closed-loop paradigm

This field aims to understand and optimize learning environments by analyzing learner data. When this process forms a dynamic cycle of "data-analysis-intervention-feedback," it constitutes the core mechanism for scalable personalized cultivation—the "closed-loop paradigm." Within the present model, learning analytics and the closed-loop paradigm function as its "nervous system" and "circulatory system," respectively. Hahn's research validates the feasibility of closed-loop learning analytics models and identifies "teacher type" and "intervention timing" as key variables [18]. AlZoubi further reveals that teachers' "sensemaking processes" regarding data dashboards act as the bridge from data to intervention within the closed loop [19]. The temporal machine learning approach developed by Nur provides an advanced data analysis tool for enabling proactive and intelligent closed loops [20]. Collectively, these studies demonstrate that the "dual-loop" system constructed in this model constitutes a complete and evolvable teaching closed-loop ecosystem. It aligns with the principles of learning science, possesses a solid technical foundation, and fully acknowledges the central role of the teacher.

(3) Data-driven decision-making and human-AI collaboration

Data-driven decision-making refers to the paradigm of formulating teaching strategies, implementing educational interventions, and optimizing teaching processes through the collection and analysis of data. Its integration with AI has given rise to a new educational ecology of "human-AI collaboration." Ji's research found that in AI-integrated teaching, the teacher's role is transformed rather than replaced, with their pedagogical authority and agency being central to effective integration [21]. The mixed-methods study by Hussain et al. confirms that the integration of AI is redefining the roles of teachers and students and reshaping learning experiences, emphasizing that AI should serve as a "tool" to enhance educational experiences [22]. This provides a theoretical anchor for the role division and collaborative relationship between teachers and AI within the present model.

In summary, these six theories form a clear, hierarchical, and mutually supportive framework, establishing a solid theoretical foundation for the "AI Dual-Loop Empowerment" model. This framework indicates that mastery learning theory defines the model's foundational goal. Constructivist and distributed cognition theories explain the internal mechanics of the "dual loops" from the perspectives of individual knowledge construction and human-AI system synergy, respectively. Building upon this, the precision education paradigm establishes the core philosophy of data-driven instruction. Learning analytics and the closed-loop paradigm provide the methodological support for realizing the closed flow of data and intervention feedback. Finally, data-driven decision-making and human-AI collaboration fundamentally delineate the functional boundaries and interactive relationships between teachers and AI within the collaborative teaching process.

3. Construction of the AI dual-loop empowerment model

3.1. Model framework and core components

The "AI Dual-Loop Empowerment" model is a data-driven, closed-loop instructional system that integrates the "student self-learning loop" and the "teacher teaching loop" (**Figure 1**). Its core components are as follows:

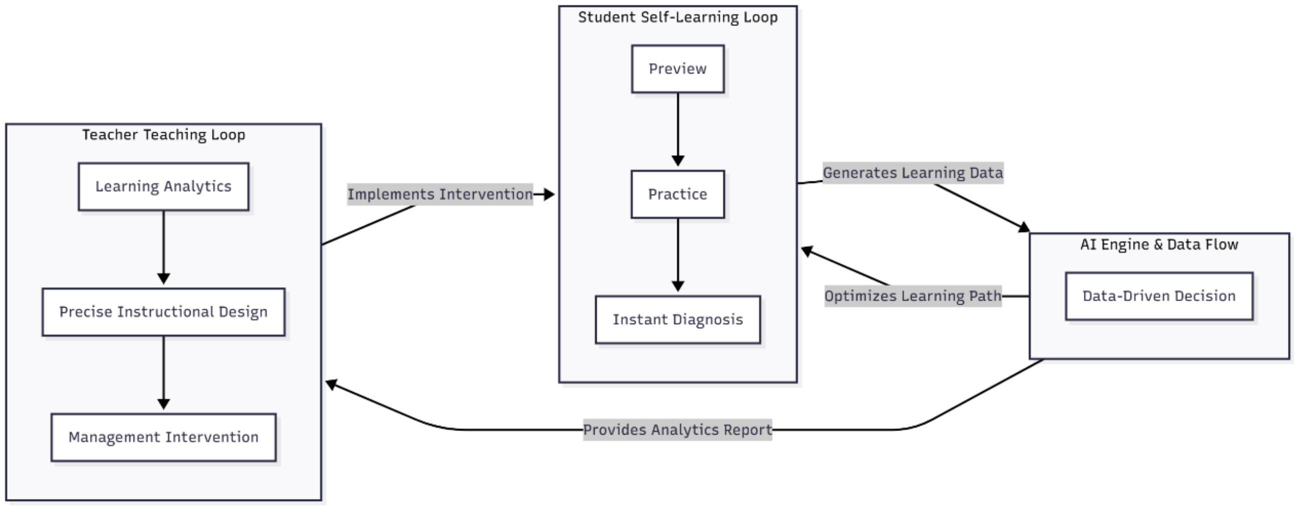

Figure 1. The AI dual-loop empowerment model.

(1) The "student self-learning loop"

This loop operates primarily during the "preview" and "practice" stages. Students use an AI platform for content preview and consolidation exercises. The platform, leveraging its built-in AI engine (e.g., machine learning models, knowledge graphs), collects and analyzes learning behavior data (e.g., video viewing duration, pause points, answer accuracy, response time) in real time. This enables "instant diagnosis" and subsequently "optimizes learning path," providing students with personalized learning support.

(2) The "teacher teaching loop"

This loop spans the entire teaching process, including lesson preparation, in-class instruction, and after-class tutoring. Teachers access the "learning analytics" report generated by the "student self-learning loop" via the platform. Based on this analysis, they conduct "precise instructional design" (e.g., adjusting teaching priorities, designing tiered tasks) and "management intervention" (e.g., individual tutoring, resource pushing). After teachers "implement intervention," the effects are fed back into the system as new data.

(3) Data flow and AI engine drive

Data serves as the core link connecting the two loops, while the "AI engine & data flow" acts as the intelligent center of the system. The learning data generated by the "student self-learning loop" is analyzed by the AI engine, which then drives teaching decisions and intervention actions within the "teacher teaching loop." Data on the effects of teacher interventions (e.g., classroom performance, assignment quality) is fed back to the "student self-learning loop," influencing subsequent diagnosis and path optimization. This process forms a continuously iterative, self-optimizing closed-loop instructional ecosystem, achieving genuine "data-driven decision."

3.2. Operational mechanism characteristics

(1) Data-driven: The model operates entirely on objective, continuous learning data, shifting teaching decisions from being experience-driven to evidence-driven.

(2) Dual-loop linkage: ”Learning” and “teaching” are tightly coupled through real-time data flow, forming an organic whole that mutually drives each other. This implements the scalable teaching mechanism of “letting learning determine teaching and letting teaching promote learning” in practice.

(3) Human-AI collaboration: The model clarifies the division of roles between AI and teachers. AI acts as a “super teaching assistant,” handling repetitive, computational tasks and providing data insights. The teacher serves as the “learning commander,” responsible for emotional guidance, cognitive stimulation, creative instructional design, and the final review of AI output, ensuring the dominance of human cognition within the system.

This framework is universal; its core mechanisms, “data-driven,” “dual-loop linkage,” “human-AI collaboration,” can be adapted to different subject contents and teaching scenarios.

4. Teaching derivation: The case of “Completing the square for quadratic equations”

To concretize the operational mechanism of the model, this study conducts a hypothetical teaching derivation using the junior secondary mathematics topic “completing the square for quadratic equations” as an example.

(1) “Student self-learning loop” (Pre-class)

Students watch an instructional micro-video on completing the square and complete fundamental exercises on the AI platform. Through ”instant diagnosis”, the platform identifies that approximately 60% of students make errors in the specific step of “handling quadratic equations where the leading coefficient is not 1,” while also flagging individual students struggling with the conceptual understanding of “perfect square trinomials.” Consequently, the system ”optimizes learning path” by pushing targeted review materials to the relevant students.

(2) Data Flow and the “Teacher Teaching Loop” (Lesson Preparation)

The teacher reviews the ”learning analytics” report and decides to focus the upcoming classroom instruction on the technique for “completing the square when the leading coefficient is not 1,” designing an inquiry-based activity around it. Simultaneously, the teacher prepares strategies for providing in-class attention and after-class tutoring plans for the identified individual students.

(3) “Teacher Teaching Loop” (In-class)

The teacher begins the lesson by introducing a real-life scenario problem. The instruction then focuses on guiding students to explore and summarize the specific steps for the targeted technique. Addressing the common error, the teacher organizes group discussions, allowing students to self-analyze and correct their misunderstandings, thereby implementing a precise teaching intervention.

(4) Closed-loop Feedback (Post-class)

The teacher assigns tiered assignments. Based on the new data from classroom performance and assignment completion, the platform regenerates the learning analytics report. This new data indicates significant improvement regarding the previously common weakness, though some individual students still require further attention. The system again ”optimizes learning path” based on this updated information, and the teacher plans the next cycle of ”management intervention.” This concludes one full cycle of the “dual-loop” process, immediately initiating a new instructional iteration.

5. Discussion and conclusion

The "AI Dual-Loop Empowerment" model constructed in this study provides a valuable supplement to existing theories of AI in education. It transcends the perspective of treating AI as a mere tool, elevating it to a core driver for restructuring the teaching process and optimizing pedagogical relationships.

5.1. Theoretical contribution

The model directly addresses the three major research limitations identified earlier. Firstly, it counters the "tool-oriented" tendency by proposing a systematic, top-down designed model. Secondly, it remedies the insufficiency of "unidirectional" research by elucidating the data interaction mechanism between the dual loops. Finally, drawing on theories like distributed cognition, it clarifies the division of roles between teachers and AI within "human-AI collaboration," thereby resolving the ambiguity surrounding its conceptual connotation. This direction aligns closely with the ICME-15 agenda of "reconstructing teaching paradigms through AI" [4].

5.2. Practical implications and future research

This model offers a clear blueprint for frontline teachers to integrate AI into their teaching practice, provides a feasible entry point for schools to advance their digital transformation, and supplies a theoretical basis for educational technology companies to optimize product design. While this study focuses on theoretical construction, the model's efficacy, adaptability to different school contexts, and long-term impact require further validation and refinement through rigorous empirical research in subsequent studies.

In summary, the "AI Dual-Loop Empowerment" model proposed herein offers a theoretically coherent and mechanistically explicit solution to the core educational contradiction of scaling standardization versus personalization. Future empirical research will be dedicated to testing its effectiveness and promoting its deeper integration and application across a wider range of educational scenarios.

Disclosure statement

The authors declare no conflict of interest.

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