The construction of the Chinese AI version of Digital Bloom (CAID Bloom)

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Abstract

This is a STUDENT paper and an Evidence-Based Practice (EBP) full paper. Generative AI (GAI) and digital technologies have fundamentally transformed global education. The classic Digital Bloom Taxonomy, localized in China in 2011, lacks coverage of GAI's dynamic capabilities (e.g., adaptive learning pathways, real-time interactive feedback) and compliance with evolving data regulations. To address this gap, this study employs an EBP methodology to construct the "Chinese AI Digital (CAID) Bloom Taxonomy by analyzing 24 representative educational AI products. Retaining Bloom's six cognitive levels, the framework systematically maps contemporary AI tools to each level, integrating functional characteristics, Technology Readiness Levels (TRL), and alignment with China's data privacy and educational policies. It provides actionable guidance for educators to select AI tools aligned with specific cognitive objectives, offers learners personalized AI resources, and supports China's educational intelligent transformation. This research extends Bloom's taxonomy to the GAI era with a policy-compatible, practice-oriented framework. Future work will empirically validate its efficacy across diverse educational contexts and explore interdisciplinary scalability.

Keywords
AI in education, Generative AI, Digital Bloom, CAID Bloom, Data Security and Compliance

1. Introduction

Driven by the widespread adoption of digital technologies and breakthroughs in GAI, global education is experiencing a paradigm shift from technology-assisted to intelligence-enhanced learning. The iterative advancement of intelligent agents and the practical deployment of embodied intelligence have further deepened AI's penetration and reconstruction of educational ecosystems through two complementary dimensions: cognitive empowerment and physical interaction. To harness these advancements, educational systems must transcend traditional human-machine paradigms, adapt to GAI-enabled capabilities (e.g., real-time content generation, personalized adaptation, dynamic feedback loops), and achieve the systematic integration of technologies with pedagogical objectives—thus mitigating risks of technological instrumentalization and blind adoption.

Andrew Churches' (2009) Digital Bloom Taxonomy[1] systematically mapped various digital tools to the six cognitive levels of Bloom's Revised Taxonomy, establishing a structured bridge between digital technologies and pedagogical goals. To address its cross-cultural incompatibility and misalignment with China's educational ecosystem, Chen and Zhu (2011)[2] developed a localized Chinese version by substituting foreign tools with domestic alternatives. However, GAI has sparked a second wave of educational technology transformation, fundamentally reshaping the boundaries of traditional digital tools: simple information retrieval has evolved into reasoning-enabled intelligent question-answering, static learning resources have advanced to dynamic adaptive systems, and emerging technologies (e.g., intelligent agents, embodied intelligence) have expanded educational AI's application scenarios—from virtual cognitive support to physical interactive practice. Today, AI technologies offer enhanced capabilities across all levels of Bloom's Taxonomy, making the existing localized framework insufficient to capture the core features and compliance requirements of contemporary educational AI tools.

More critically, China has established a multi-layered regulatory framework governing the digital economy and educational intelligence, with policies imposing stringent requirements on educational AI. Enacted in 2021, the *Data Security Law* and *Personal Information Protection Law* mandate guardian consent for processing minors' personal information and require enhanced security measures, imposing rigid constraints on data collection and usage of educational AI products. In 2023, the Ministry of Education's *Opinions on Strengthening Science Education in Primary and Secondary Schools in the New Era*[3]emphasized leveraging AI to innovate science education content and forms, while stressing adherence to educational laws and students' physical and mental development characteristics. Implemented in 2024, the *Safety Specifications for the Application of Artificial Intelligence in the Field of Education*[4] established mandatory technical standards for data security, algorithmic security, content security, and privacy protection. Notably, neither the original Digital Bloom Taxonomy nor its Chinese localized version integrates these regulatory constraints, rendering them ill-suited to the practical demands of China's educational intelligent transformation.

Against this backdrop, this study examines the functional characteristics and hierarchical distribution of Chinese educational AI products in the GAI era. Adopting an EBP methodology, this research is divided into three key phases: evidence collection, evidence integration, and evidence evaluation. Furthermore, it develops a localized classification framework-the CAID Bloom Taxonomy, which balances three core dimensions: cognitive goal alignment, technology maturity (assessed via Technology Readiness Level, TRL), and compliance with data security regulations. Ultimately, this research aims to provide actionable guidance for educators, learners, and product developers in selecting appropriate educational AI tools, while offering theoretical and practical insights to facilitate the intelligent transformation of education in China.

2. Literature Review

2.1 Evolution and Localization of the Digital Bloom Taxonomy

Since its introduction in 1956, Bloom's Taxonomy of Educational Objectives has served as a foundational theoretical tool for designing educational goals and conducting teaching evaluations. With the proliferation of digital technologies in education, Andrew Churches (2009)[1] proposed the Digital Bloom Taxonomy, which for the first time mapped various common digital tools (e.g., search engines, mind mapping software, video editing tools) to the six cognitive levels of Bloom's Revised Taxonomy: Remembering, Understanding, Applying, Analyzing, Evaluating, and Creating. This framework provided an intuitive operational guide for technology-enhanced teaching and fostered the standardized development of digital education. However, subsequent research has identified significant cultural limitations and technological obsolescence: first, the included tools are predominantly foreign platforms, exhibiting poor adaptability to non-English educational ecosystems; second, it fails to incorporate emerging technologies and overlooks cross-national compliance requirements (e.g., data security, privacy protection).

To address these limitations, Chinese scholars Chen and Zhu (2011) [2] localized the Digital Bloom Taxonomy by replacing foreign tools with domestic alternatives (e.g., browsers, video platforms, search engines, mind mapping software), emphasizing digital literacy training tailored to the Chinese context. Despite these improvements, the Chinese version lacks a systematic compliance evaluation framework and technology maturity assessment mechanism. Moreover, it remains limited to functional mapping of traditional digital tools, failing to capture core GAI characteristics (e.g., dynamic content generation, adaptive learning path planning) and lacking systematic evaluation of technology maturity and regulatory compliance—thus limiting its utility for practical tool selection.

2.2 Integration of Generative AI and Bloom's Taxonomy

Generative AI has revolutionized education, with its application value across all cognitive levels of Bloom's Taxonomy widely validated. Research demonstrates that technologies such as Large Language Models (LLMs) and multimodal generation enable rapid knowledge retrieval and memory consolidation at lower cognitive levels, while supporting complex problem analysis and innovative content creation at higher levels, forming a full-chain cognitive enhancement framework[5]. The emergence of intelligent agents and embodied intelligence has further expanded these integration boundaries: educational intelligent agents dynamically plan personalized learning paths through autonomous perception, decision-making, and interaction; embodied intelligence, leveraging physical carriers (e.g., educational robots), constructs integrated "cognition-behavior" learning experiences in practical, scenario-based teaching. The application of GAI in education must transcend tool-substitution logic and adopt a human-AI collaborative cognitive enhancement paradigm. Clarifying the division of roles between humans and AI at each cognitive level is critical to preventing GAI from being reduced to a mere "cheating tool" [6].

In terms of theoretical construction, Jain and Samuel (2025) [7] proposed the "Bloom Meets Gen AI" framework, advocating that cognitive skills be conceptualized as interconnected nodes rather than rigid hierarchical structures. They emphasized incorporating process-oriented measurements in evaluations to capture the complexity of AI-facilitated cognitive engagement. However, this framework overlooks technology maturity and regional policy adaptability. Duong-Trung et al. (2024)[8] developed BloomLLM, a system that employs supervised fine-tuning of LLMs to generate assessment items aligned with each level of Bloom's taxonomy, underscoring the necessity of aligning AI outputs with established educational frameworks for meaningful cognitive engagement. Singh et al. (2024) [9] proposed an Explainable AI governance framework for education, which emphasizes transparency, interpretability, and accountability in AI systems. While it addresses the crucial aspect of explainability, it lacks direct alignment with Bloom's taxonomic structure and does not fully resolve issues related to product stability and large-scale deployment.

Against this backdrop, the Reverse Bloom's Taxonomy has emerged as a pivotal theoretical shift in AI education, challenging the traditional bottom-up cognitive progression. Recognizing GAI's dominance in low-order tasks, Ayodele et al. (2026)[10]formalized a Dual-Mode Cognition framework — commonly termed "augmented cognition" — which advocates beginning with higher-order skills (Creating, Evaluating, Analyzing) while leveraging AI to automate low-order acquisition, thereby freeing learners for deeper engagement. A meta-analysis by Wang & Fan (2025)[11] provided empirical validation, demonstrating that students employing this reversed approach achieved approximately 32% higher mastery of higher-order cognitive tasks compared to traditional learners.

In empirical research, Gao and Li (2024)[12] examined the answer quality of GPT-3 and Google across Bloom's Taxonomy levels, finding that AI performs well in lower-order tasks but requires human guidance for higher-order tasks. Chan and Wong (2025)[13] demonstrated that GAI can achieve human-level performance in evaluation and creation tasks, such as English literature analysis. Conati et al. (2024)[14] conducted a quasi-experimental study showing that AI tools aligned with cognitive goals improve learning outcomes, though tool selection's scientificity and compliance directly impact efficacy. Empirical studies on intelligent agents and embodied intelligence have validated embodied intelligent robots' value in K-12 education, including remote interaction, inclusive teaching, and embodied AI enlightenment, providing insights for STEM training scenarios[15]. A recent review by Liu et al. (2024)[16] constructed a unified framework for embodied intelligence, characterized by "morphology-action-perception-learning" synergy. This framework synthesizes existing research and highlights the lack of unified classification standards and prominent fragmentation in educational research on embodied intelligence and intelligent agents.

3. Research Methods and Data

To ensure the rigor and practicality of the CAID Bloom Taxonomy construction, this study adopts an EBP methodology, which is explicitly structured into three sequential phases. Below is a detailed overview of the research methods and data sources employed.

3.1 Research Methods

EBP involves systematically collecting, evaluating, and integrating empirical evidence to develop theoretical frameworks that guide practice. Characterized by a strong empirical orientation and practical value, EBP has been widely adopted in fields such as educational technology and healthcare[17]. This study adapted the EBP methodology for constructing the CAID Bloom Taxonomy, dividing the process into three phases: (1) Evidence Collection:

Systematically gathering multi-source evidence, including functional data of educational AI products, policy documents, and academic research findings, to ensure comprehensiveness and authority; (2) Evidence Integration: Using Bloom's Revised Taxonomy as the theoretical anchor, iteratively integrating multi-source evidence to develop the initial hierarchy and dimensions of the framework; (3) Evidence Evaluation: Recruiting 4 frontline teachers (≥5 years of experience), 3 educational AI enterprise leaders (focusing on K-12/higher education), and 3 college/high school students to validate the framework's hierarchical logic, product matching accuracy, and application feasibility through semi-structured interviews, ultimately refining the CAID Bloom.

3.2 Data Sources

This study draws on three primary data sources: (1) Educational AI Enterprises and Products: Based on authoritative sources, including the Ministry of Education's filing list of educational informatization products and download rankings of mainstream app stores, 24 representative C-end products were selected via purposive sampling, covering multiple educational stages and scenarios (e.g., language learning, programming education, academic research); (2) Public Platform Information: Product functional characteristics and application scenarios were collected from enterprise official websites, product white papers, and app store descriptions; (3) Policy and Compliance Documents: Relevant policies (e.g., the Personal Information Protection Law, the Guidelines for the Application of AI in the Field of Education) were systematically reviewed, and compliance evaluation indicators were extracted, covering data security, algorithmic security, and content security (see Table 1).

Table 1. Representative Educational AI Products and Enterprise (Partial Sample)

Enterprise Name	Product Name	Core Functions	Target Educational Field	Official Website
DeepSeek	DeepSeek AI Creative Assistant	Multimodal idea inspiration, prototype design support, academic framework generation	Higher Education, Vocational Education	https://www.deepseek.com
Duolingo	Duolingo Max	Q&A support, role-playing, video call oral practice, personalized feedback	Language Learning (All Stages)	https://www.duolingo.com
iFLYTEK	iFLYTEK Spark AI Writing Assistant	Academic paper writing support, chart description composition, format optimization	Higher Education, Vocational Education	https://xinghuo.xfyun.cn
UBTECH	UBTECH AI Educational Robot	Programming, STEM project practice, interactive scenario-based learning, hands-on skill training	K-12 Education, Vocational Education	https://www.ubtrobot.com
CNKI	CNKI AI	Bibliometric analysis, research	Higher Education,	https://ww

	Academic Assistant	hotspot identification, citation relationship mapping	Scientific Research	w.cnki.net
ByteDance	Doubao	Oral practice, step-by-step problem-solving, writing assistance	All Educational Stages	https://www.doubao.com/chat

Note:Entries are sorted alphabetically by the pinyin of enterprise names.

4. Construction of the CAID Bloom Taxonomy

4.1 Core Dimensions of the Framework

This study collected data on the functional characteristics, application scenarios, technology maturity, and compliance of the aforementioned products. Technology maturity was assessed using the TRL scale (Levels 1–9)[18], with evaluations integrating three key indicators: product commercialization scope (e.g., pilot testing, full-platform deployment), user scale and stability data from public reports, and inclusion in regional or school-level procurement lists. Compliance was categorized as "compliant" or "non-compliant" based on relevant regulations, with non-compliant products excluded from the framework. The selected products were mapped to the six cognitive levels based on their core functions, forming the initial structure of the CAID Bloom Taxonomy (see Table 2).

Table 2. Core Dimensions of the CAID Bloom Taxonomy

Cognitive Level	Typical Teaching Scenarios	Core AI Technical Features	TRL Range	Compliance Requirements
Remembering	Knowledge recitation, vocabulary memorization, error consolidation	Retrieval-based LLM + flashcard generation + adaptive spaced repetition algorithm	7–8	Local data storage; encrypted desensitization of minors' personal information
Understanding	Concept explanation, knowledge organization, interdisciplinary correlation	Multimodal LLM + knowledge graph + interactive visualization technology	7–8	Information security assessment certification; hierarchical user data authorization mechanism
Applying	Experimental operation, exercise training, vocational skill simulation	LLM + simulation engine + dynamic task generation + real-time interaction feedback	6–7	End-to-end encrypted data transmission; regular compliance audits
Analyzing	Error analysis, bibliometrics, learning diagnosis	Automated evaluation +data visualization+AI agent logical reasoning assistance; embodied AI data feedback analysis	6–7	Learning behavior data protection; explicit privacy policies; AI agent algorithms' interpretability; controllable embodied AI data collection
Evaluating	Homework grading, project review,	Evaluation criteria model + structured feedback +	6–7	Traceable scoring data; transparent AI evaluation

	competency level assessment	learning path recommen -dation; AI agent multi dimensional evaluation; embodied AI scoring		standards; encrypted storage of embodied AI data
Creating	Academic writing, creative design, interdisciplinary project planning	Generative multimodal, inspiration algorithm;AI agent collaborative creation; embodied AI prototype testing	7–8	Copyright protection for generated content; adult supervision required for minors' use; traceable creation process for AI agents

By deeply integrating cognitive goals, AI technologies, and policies/regulations, the CAID Bloom Taxonomy establishes a dynamically adaptive closed loop encompassing goal orientation, technical support, and boundary constraints. This loop enables the alignment of tasks at different cognitive levels with corresponding technologies and institutional environments: cognitive goals define the direction for technology and compliance adaptation, AI technologies determine the feasibility of achieving cognitive goals, and policies/regulations mitigate risks associated with technological application (see Figure 1).

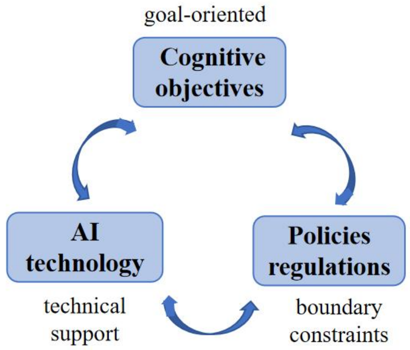

Figure 1 Dynamic Adaptive Closed-Loop of CAID Bloom Elements

Specifically, tasks at lower cognitive levels (Remembering-Understanding) are characterized by high universality and broad user coverage, focusing on data security baselines, including localized data storage and desensitization of minors' information. These tasks are matched with high-maturity products (TRL 7–8) to ensure stability and minimize cognitive load. Tasks at middle and higher cognitive levels (Applying-Analyzing-Evaluating) feature prominent personalized needs and high problem complexity. Beyond data security, they require multiple constraints (e.g., full-process traceability, content compliance reviews) and are paired with TRL 6–7 products to achieve dynamic balance in complex scenarios. Tasks at the Creating level prioritize innovative output and achievement transformation, focusing on property requirements such as copyright protection and compliance audits. Driven by industry demand, products at this level exhibit high maturity; however, minor users require teacher or parent supervision. Thus, it is adapted to high-maturity product solutions (TRL 7–8).

Notably, the adaptation mechanism at each level is not static but dynamically optimized alongside updates to policies/regulations and the evolution of AI technologies, ensuring the framework's long-term adaptability.

4.2 AI Product Mapping at Each Cognitive Level

Subsequently, 10 participants (4 teachers, 3 AI enterprise leaders, 3 college/high school students) were recruited via purposive sampling. Their feedback on the CAID Bloom was collected through WeChat, focusing on verifying the rationality of product classification, accuracy of dimension descriptions, and feasibility of application pathways. The framework was revised and refined based on this feedback.

Participants generally acknowledged that the framework features clear product mapping, hierarchical resource recommendations aligned with the needs of different learning stages, and that the compliance and TRL dimensions provide benchmarking guidance for product R&D. They also proposed several improvement suggestions, including adjusting the functional boundaries between the Applying, Analyzing, and Evaluating levels, and supplementing compliance details regarding the "minor supervision mechanism" at the Creating level. The revised CAID Bloom incorporates 24 representative educational AI products, covering mainstream technical forms and application scenarios in China’s current educational market (see Figure 2). The blue bottom section denotes products requiring special adult supervision for minor users.

Figure 2. CAID Bloom Taxonomy

As illustrated in Figure 2, educational AI products exhibit a dual-track distribution pattern: "vertical deepening" and "full-stack coverage." Tool-based products (e.g., Duolingo) focus on specific cognitive levels (e.g., Remembering, Understanding) to achieve in-depth adaptation of corresponding functions. In contrast, general or education-specific LLMs (e.g., DeepSeek, Doubao) offer full-stack coverage across multiple cognitive levels, extending from knowledge interpretation at the Understanding level to multimodal content creation at the Creating level, breaking the single-functional boundary of traditional educational tools. Additionally, the Applying, Analyzing, and Evaluating levels demonstrate a certain degree of functional integration: many products at these levels possess composite functions, such as scenario simulation, logical decomposition, learning resource retrieval, and competency assessment. The autonomous decision-making of intelligent agents and physical interaction of embodied intelligence further reinforce this integration, reflecting the scenario-driven integration trend of educational AI products.

Remembering Level： The core goal of this level is to help learners accurately acquire and deeply consolidate basic knowledge, while enabling rapid retrieval and long-term retention of knowledge. Educational AI products at this level are characterized by LLM-based knowledge extraction, automatic flashcard generation, and optimization of adaptive spaced repetition algorithms, reducing memory load and improving knowledge retention efficiency through technical means. For instance, Baicizhan employs AI-driven adaptive spaced repetition algorithms and LLM-powered multimodal contextual memory (text and images), offering functions such as personalized error diagnosis and targeted reinforcement of weak points to support learners in English vocabulary accumulation and exam preparation. Widely commercialized in China (TRL 8), it adopts a hierarchical data protection mechanism for minors, realizing anonymization of user personal information and local encrypted data storage to meet compliance requirements.

Understanding Level： The core goal of this level is to assist learners in decomposing concept connotations, constructing knowledge association networks, and deepening their understanding of knowledge essence. Educational AI products at this level feature interactive explanation, knowledge visualization, and structured organization, leveraging multimodal forms (e.g., text, audio, animation) to lower the threshold for understanding abstract concepts. For example, the NetEase Youdao AI Learning Assistant offers functions such as hierarchical explanation of knowledge points, contextual listening and speaking training, and error-concept tracing, supporting language learning and comprehension of science concepts. Launched across all platforms (TRL 8), it employs encrypted data transmission and special protection for minors' information, complying with educational data security specifications.

Applying Level： The core goal of this level is to enable learners to transfer mastered knowledge to specific problem scenarios and enhance their knowledge application capabilities through practical operations. Educational AI products at this level are defined by scenario simulation, interactive simulation, and dynamic exercise generation, improving knowledge transfer and application efficiency via immersive interactive experiences. For example, Coding Cat provides K-12 programming enlightenment, advanced code programming learning, and informatics competition preparation through AI real-time code diagnosis, intelligent error correction, and LLM-driven scenario-based project development. Leveraging a matrix of graphical programming tools and an AI interactive teaching system, it has achieved large-scale commercialization in K-12 education scenarios (TRL 7), adhering to encrypted data storage specifications and clarifying copyright ownership of user works.

Analyzing Level： The core goal of this level is to assist learners in decomposing complex problems, identifying key elements and internal logical relationships, and extracting underlying problem patterns. Educational AI products at this level are distinguished by logical reasoning assistance, error pattern diagnosis, and learning data visualization-with intelligent agents' reasoning capabilities and embodied intelligence's data feedback analysis further enhancing analytical efficiency. For instance, the CNKI AI Academic Analysis Assistant offers functions including bibliometric analysis, research hotspot and trend visualization, and citation relationship mapping, which have been widely deployed in academic research and paper writing. Primarily used in institutions of higher education (TRL 7), it ensures compliant use of literature data and encrypted storage of user research data, fully adhering to data security specifications for scientific research contexts.

Evaluating Level： The core goal of this level is to enable learners to make objective judgments on target objects and propose evidence-based improvement suggestions. Educational AI products at this level are characterized by evaluation criterion matching, fine-grained feedback generation, and personalized improvement plan recommendation-with intelligent agents' multi-dimensional evaluation and embodied intelligence's practical performance scoring further enhancing the fairness and pertinence of assessments. For example, the Liulishuo AI Language Proficiency Evaluation System leverages educational LLMs and language proficiency frameworks to conduct objective quantitative scoring of oral expression (e.g., pronunciation accuracy) and written composition (e.g., grammatical standardization), accurately identifying pronunciation deviations and grammatical errors. Pilot-promoted in language education contexts (TRL 6–7), it incorporates an AI algorithm fairness optimization mechanism, featuring transparent evaluation dimensions and scoring rules, as well as traceable and interpretable algorithmic decision paths, satisfying dual regulatory requirements for user privacy protection and learning data security.

Creating Level： The core goal of this level is to empower learners to generate novel and valuable original outputs and break through creative thinking constraints. Educational AI products at this level are defined by multimodal content generation, idea inspiration, and prototype design assistance-with AI agents' collaborative creation and embodied intelligence's prototype construction expanding creative boundaries via generative technologies. Its core value lies in fostering learners' innovative thinking and creative capabilities, enabling the transformative leap from knowledge absorption to knowledge production. For example, DeepSeek can automatically generate writing outlines, project plans, and STEAM work design frameworks, integrating interdisciplinary knowledge to develop cross-field creation schemes and lowering the creative threshold (see Figure 3). Widely commercialized (TRL 8), it mandates guardian supervision for minors' creative content generation, and its algorithmic interpretability fully complies with relevant regulatory requirements.

4.3 Cross-Level Coverage and Differentiated Adaptation of LLMs

Educational AI products leverage end-to-end capabilities of LLMs to achieve comprehensive

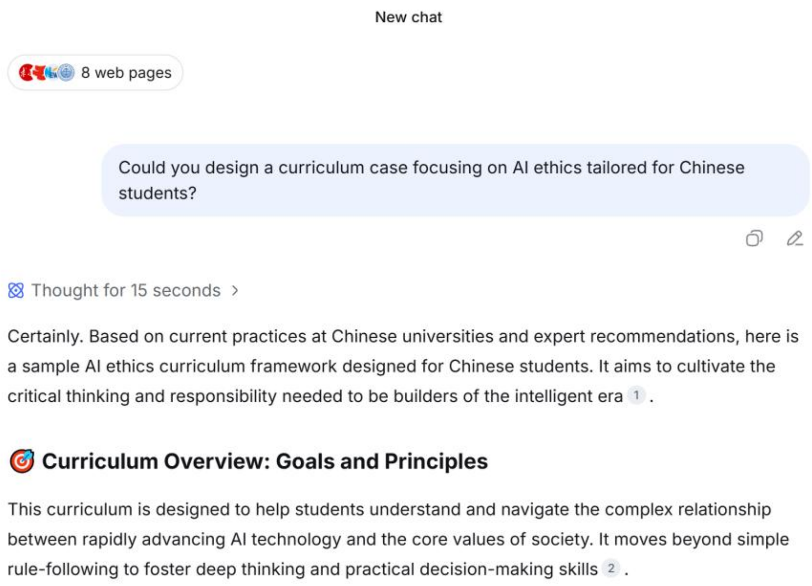

Figure 3. AI Creation Capabilities of a LLM

coverage and in-depth linkage across Understanding, Applying, Analyzing, and Evaluating levels. As a high-order cognitive capability, creation is not isolated but relies on synergistic support of all lower-level cognitive functions. Meanwhile, LLMs applied in creation scenarios can reversely invoke core capabilities from each level, forming a closed-loop learning cycle. Specifically, in the idea construction phase, knowledge association and structured organization capabilities of the Understanding level can be harnessed to build a logically rigorous creation framework; in the practical creation phase, scenario simulation and interactive experience capabilities of the Applying level can be integrated to deliver an immersive creation process; in the content optimization phase, logical decomposition and pattern extraction capabilities of the Analyzing level can be employed to diagnose logical gaps missing elements creation; in the achievement polishing phase, standard matching and fine-grained feedback capabilities of the Evaluating level can be leveraged to provide targeted optimization suggestions with creation specifications.

Currently, numerous educational AI products implement secondary development by integrating foundational LLMs (e.g., DeepSeek). These products retain LLMs' strengths in creative output while conducting targeted optimizations for educational scenarios, and satisfy compliance constraints and content alignment requirements for educational data. Nevertheless, LLM applications at the Creating level necessitate clear delineation of human-AI collaboration boundaries: AI undertakes low-cognitive-load auxiliary tasks such as idea inspiration and prototype construction, while learners take charge of in-depth content refinement, core innovative value extraction, and final intellectual property rights confirmation. This approach not only upholds AI's role as a "cognitive scaffold" but also anchors learners' central position in innovative practice—aligning perfectly with the "human-AI collaborative cognitive enhancement" paradigm.

4.4 Adaptation Characteristics of Intelligent Agents and Embodied Intelligence

The dynamic closed loop of intelligent agents and embodied intelligence operates across multiple cognitive levels and is oriented toward specific cognitive objectives (see Figure 4).

LLM-based intelligent agents are applicable across all educational stages, supporting personalized learning, multi-turn interactive Q&A, and autonomous learning path planning. These products have achieved large-scale commercialization, with mature interaction logic and robust content adaptation capabilities. The primary compliance priorities for intelligent agent products are algorithmic decision transparency and data traceability, requiring that the logic underpinning autonomous recommendations, evaluations, and other functions be fully interpretable and compliant with algorithmic fairness standards.

Embodied intelligence products target practical, scenario-driven teaching scenarios, such as K-12 STEM experiments, vocational education skill training, and special education sensory training, enhancing learning experiences and outcomes through physical space interactions. Due to constraints including hardware costs and scenario adaptation complexity, these products exhibit differentiated technology maturity: simple embodied intelligence products for K-12 education (e.g., programming robots) have reached TRL 7, while complex practical embodied intelligence products for vocational education (e.g., industrial robot training equipment) remain mostly in the TRL 6 pilot phase. Key compliance priorities for embodied intelligence products include desensitization of environmental perception data, safety control of operational behaviors, and controllable limits on data collection scope, which jointly mitigate privacy leakage and physical interaction safety risks.

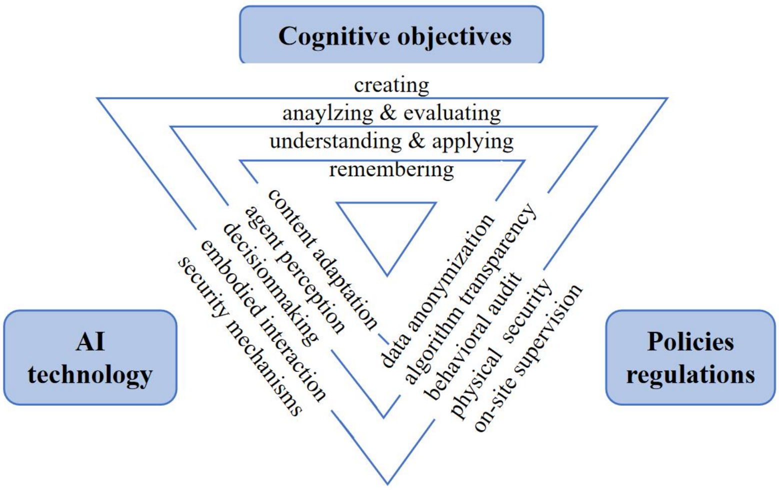

Figure 4. Dynamic closed-loop of agents and embodied intelligence

5. Practical Guidance Strategies for the Framework

The CAID Bloom offers differentiated practical guidance for educators, learners, and AI enterprises, forming a collaborative optimization closed loop integrating teaching application, autonomous learning, and product R&D. It also provides targeted guidance strategies for emerging products including intelligent agents and embodied intelligence systems.

5.1 Educators: Precise Technology Selection and Human-AI Collaborative Design

Educators should define clear technology selection and teaching design strategies for educational AI products. For teaching activities aligned with specific cognitive levels of Bloom's Taxonomy, they are advised to select products with matching functions and a technology maturity level of TRL 6 or above from the corresponding tier of the framework. Concurrently, educators should regularly verify product compliance with requirements such as localized data storage, encrypted data transmission, and user authorization revocation, and update tool selection plans each semester based on learning outcome data and product iteration progress. In the teaching design and implementation process, educators should first identify the Bloom's cognitive level corresponding to teaching objectives, select functionally matched products from the framework's corresponding level, design human-AI collaborative teaching activities (e.g., using AI tools to generate concept maps, with teachers guiding students to deepen conceptual understanding), collect learning outcome data (e.g., concept mastery test scores, student feedback), and iteratively optimize tool selection.

5.2 Learners: Hierarchical Personalized Learning Resource Adaptation

The CAID Bloom Taxonomy provides learners with a phased, personalized guideline for intelligent resource utilization. For example, in the foundational stage (Remembering-Understanding), learners can use intelligent flashcards and multimodal explanation tools to consolidate basic knowledge; in the proficiency stage (Applying-Analyzing), they can employ simulation experiments and error diagnosis tools to enhance practical and analytical capabilities; in the advanced stage (Evaluating-Creating), they can leverage evaluation feedback tools and generative creation systems to foster critical thinking and innovation capabilities. Additionally, all products included in the framework have undergone rigorous compliance reviews, ensuring robust protection of learners' data privacy. When using embodied intelligence products, learners must adhere to operational safety protocols; when using intelligent agent products, they should pay close attention to the scope of personal data authorization.

5.3 Educational AI Enterprises: Compliance-Oriented R&D and Scenario Depth

For AI enterprises, the CAID Bloom Taxonomy further clarifies product compliance design and function optimization strategies. Enterprises should focus on core needs of specific cognitive levels, avoid product functional generalization, and enhance product adaptability to teaching scenarios; product R&D should achieve a minimum TRL 6 maturity level to ensure application stability; and products must meet regulatory requirements including localized data storage, privacy protection, and compliant copyright usage. For intelligent agent products, enterprises need to enhance algorithm interpretability and decision transparency, and establish boundary control mechanisms for personalized interactions. For embodied intelligence products, enterprises should optimize hardware adaptability and scenario-specific functions, and strengthen compliant design for environmental data collection, such as adopting technical measures including data desensitization and collection scope limitation.

Additionally, enterprises should strengthen collaboration with educational institutions to conduct targeted teaching scenario adaptation tests, enhance the practical teaching value of products, provide standardized references for product R&D, and contribute to the overall quality and adaptability improvement of educational AI products.

6. Conclusion

The construction of the CAID Bloom Taxonomy is subject to three main limitations. First, product coverage is constrained: the framework currently prioritizes mature products from mainstream enterprises, with insufficient representation of innovative solutions from start-ups or specialized tools for niche disciplines such as arts and special education. Second, empirical validation remains limited: large-scale, multi-regional, and interdisciplinary teaching studies have yet to be conducted to verify the framework's effectiveness in improving learning outcomes and teaching efficiency. Third, interdisciplinary adaptability requires further refinement: discipline-specific product recommendations and application strategies tailored to the cognitive characteristics of humanities, sciences, and arts have not yet been developed.

To address these limitations, future research will expand the product sample to include emerging tools from start-ups and specialized domains, conduct large-scale empirical studies across regions and disciplines to validate the framework's efficacy, and develop discipline-adaptive strategies to enhance its practicality and generalizability.

Despite these limitations, this study makes a significant contribution by integrating technology maturity and data security compliance into a classification framework for educational AI. Grounded in the EBP methodology and synthesized from multidimensional data on 24 mainstream educational AI products, the CAID Bloom Taxonomy 2.0 achieves a systematic integration of cognitive objectives, AI technological features, and regulatory policies. It overcomes key limitations of the traditional Digital Bloom Taxonomy, particularly its inadequate cross-cultural adaptability and lack of compliance considerations, while systematically incorporating, for the first time, the characteristics and compliance requirements of emerging technologies such as intelligent agents and embodied intelligence. The framework offers educators precise guidance for technology selection, supports learners with personalized and compliant learning pathways, and provides AI developers with clear direction for scenario-driven, compliance-oriented product design. As such, it holds substantial promise for advancing a human-AI collaborative educational ecosystem.

Looking forward, to keep pace with rapid AI iteration, the framework will be refined to support dynamic learning pathways adapting to the evolving technological landscape. This includes developing mechanisms for continuous curriculum updates and real-time competency assessment, enabling educators and learners to navigate fast-changing AI tools. In parallel, the research will explore strategies for fostering AI literacy among educators and learners, emphasizing critical thinking and ethical awareness in the AI era. By embedding these considerations, the framework aims to empower educational stakeholders to leverage AI effectively while maintaining a human-centered approach to education.

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