Hybridizing adaptive intelligent tutoring systems with generative AI: challenges and opportunities for large-scale deployment and pedagogical impact

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Abstract. This article introduces GAIMHE (Generative AI and Hybrid Models for Education), an industrial–academic large-scale project that hybridizes adaptive Intelligent Tutoring Systems (ITS) with generative AI to enable scalable and pedagogically grounded personalization in K–12 education. While classical ITS provide robust adaptive sequencing based on validated learning models, they require substantial manual content production. Conversely, large language models enable scalable content generation and real-time natural-language interaction, but raise concerns regarding reliability, pedagogical alignment, computational cost, and environmental impact.

GAIMHE proposes a hybrid architecture that combines the strengths of structured ITS with generative AI, while maintaining human expertise at the core of all implementation stages. Learning trajectories remain orchestrated by a validated adaptive ITS framework (already deployed in tens of thousands of classrooms), whereas generative models support large-scale exercise production and adaptive within-exercise guidance under explicit instructional constraints.

The paper outlines an implementation process grounded in research from AI and cognitive science applied to education, including scalable content generation, adaptive hint and feedback production, quality control procedures, human validation workflows, sustainability considerations, and progressive deployment in authentic school environments.

We further examine the challenges of industrialization: ensuring quality assurance at scale, balancing scalability with pedagogical rigor, fostering teacher adoption, managing computational resources, and developing an open-science ecosystem that promotes transparency and cumulative progress in AI in Education.

Keywords: ITS · generative AI · Hybrid approach · Content and feedback generation.

1 Description of the AIED implementation, practice or policy

1.1 Challenges and opportunities in deploying large-scale AI-based educational technologies that have impact

Education systems face declining student engagement and achievement, particularly in language and mathematics (see PISA). Research demonstrates that personalized learning improves motivation and performance while addressing student diversity [11,26]. Yet increasing class sizes constrain teachers' ability to implement such approaches, motivating the development of scalable digital tools.

For several decades, Intelligent Tutoring Systems (ITS) have operationalized personalized learning through the combination of expert-designed content and adaptive algorithms [2,21]. Methods like knowledge tracing and item response theory have been used to estimate latent skill levels and personalize sequences of exercises accordingly [34,33,1,6]. While such approaches enable structured adaptation, they require extensive manual authoring of content and feedback, making large-scale expansion costly and slow.

Generative AI has opened new possibilities for learning personalization [16], notably through natural-language interaction and prompt-based tutoring with large language models (LLMs). As these systems promise flexibility and scalability, tutor-like interfaces in domains such as languages, mathematics, and programming have been explored [12,20].

However, current evidence indicates that fully generative tutor-like systems face substantial limitations for classroom-grade deployment. LLMs may generate factual inaccuracies, overprovide answers, and inadvertently reduce productive cognitive effort [13,28,35]. These issues are linked to intrinsic reliability limitations and to the scarcity of authentic tutor-student interaction data in training corpora [29,18,12,20]. Furthermore, personalization with conversational tutor typically happens within a single learning activity, rather than across full curricula, as indeed off-the-shelf generative AI systems were not trained to predict and generate adaptive curricula. In addition, rigorous classroom evaluations remain limited, with some reports pointing to mixed or negative effects on motivation and learning gains [20,4,5]. In parallel, generative AI is increasingly used to assist teachers with producing exercises and lesson materials. While such tools can accelerate content generation, they typically do not implement personalized learning trajectories or adaptive sequencing algorithms.

Globally, large-scale reliance on high-capacity models raises concerns regarding pedagogical controllability, transparency, computational cost, and environmental footprint compared to traditional ITS approaches. A common limitation across many initiatives is the lack of methodological transparency and shared datasets, which hinders robust evaluation and cumulative scientific progress.

Overall, current ITS offer effective and frugal personalization but are constrained by manual content production. Fully generative tutor-like systems offer flexibility and scalability but face major limitations: weak pedagogical alignment, factual errors, limited teacher control, poor fine-grained adaptation, and high energy costs. The GAIMHE (Generative AI and Hybrid Models for Education) project, led by an educational technology company in collaboration with an academic lab and two educational NGOs, addresses those issues through a hybrid architecture. Pedagogical structure and sequencing remain governed by validated ITS algorithms, preserving explicit learner modeling and instructional coherence. Exercises, hints, and feedback are largely pre-generated using generative models under explicit didactic constraints and systematic human validation. In targeted situations, small, specialized language models (SLMs) may provide constrained real-time support, enabling fine-grained adaptation while maintaining frugality and control. Importantly, the project aims to evaluate this approach in real classrooms, and is committed to share methods, protocols, and curated datasets as digital commons. By doing so, it seeks not only to scale personalization, but also to strengthen transparency, comparability, and cumulative progress in AI-supported education.

1.2 AI-based personalization in a graph-based Intelligent Tutoring System: approach and deployment at EvidenceB

Outline of the existing ITS EvidenceB develops adaptive learning platforms for foundational numeracy and literacy in K–12, including Adaptiv'Math[3] and Adaptiv'Langue[4]. Deployed in over 5,000 schools in France and abroad, the platform complements the standard curriculum, supporting remediation, consolidation, and enrichment aligned with official standards. Students use it in class or at home, individually or in pairs, while teachers access a dashboard summarizing progress and difficulties.

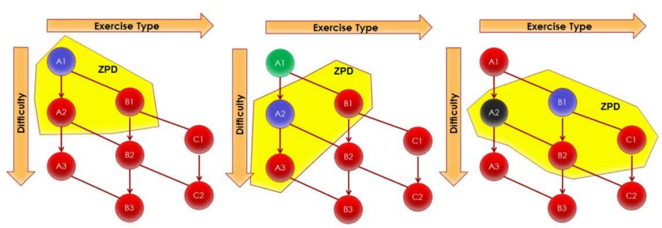

Fig. 1. ZPDES graph functioning

Algorithms and pedagogical structure. The exercise corpus is developed by pedagogy and cognitive science experts and grounded in contemporary findings in psychology and cognitive sciences [17,15]. Exercises are organized as interconnected graphs structured into modules, objectives, and activities. Sequencing

[3] https://evidenceb.fr/produits/adaptiv-math/%7D%7D

[4] https://evidenceb.fr/produits/adaptiv-langue/%7D%7D

is driven by ZPDES, a multi-armed bandit reinforcement-learning framework [8,9], grounded in Learning Progress theory and curiosity-driven learning models [22,14]. The recommendation engine selects subsequent tasks to maximize expected learning progress [14] (Figure 1). In addition, students are dynamically grouped via clustering over performance indicators (e.g., success rates, mastered objectives, time-on-task), and the resulting group descriptions are displayed in the teacher dashboard to support targeted pedagogical intervention.

Evidence of impact. Large-scale field studies report that this graph-based architecture and adaptive sequencing improve learning outcomes and motivation [8,9,24,25]. A recent randomized controlled trial involving 500 Grade 4 students across 12 academies further substantiates these findings [24,25]. The study compared three conditions: (i) AI-personalized sequencing, (ii) a non-adaptive condition using the same expert-designed content, and (iii) a business-as-usual control group. Results indicate that students in the AI-personalized condition significantly outperformed both comparison groups and showed greater reductions in achievement gaps between higher- and lower-performing students, as well as between boys and girls. Beyond France, international deployments in Côte d'Ivoire[5] and the United States (Michigan) have been accompanied by field evaluation reports indicating similar positive learning trends.

Current limitations motivating GAIMHE. Despite its effectiveness, the approach faces two bottlenecks. First, ZPDES requires dense, carefully curated graphs, implying substantial manual content production (EvidenceB ITS includes over 40,000 expert-authored exercises). Second, although sequencing is personalized, feedback remains largely generic and does not adapt systematically to error patterns or learner profiles. Personalization could be enhanced through progressive hints that support strategy development and reinforce students' sense of guidance throughout their learning journey.

1.3 Hybridizing adaptive intelligent tutoring systems with genAI: the GAIMHE project

GAIMHE extends this deployed ITS architecture through the integration of generative AI, combining scalability with pedagogical control 2. The design is organized around two complementary pillars.

At the macro level, exercises and feedback are pre-generated using LLMs under explicit pedagogical specifications, then validated and integrated into the existing ITS infrastructure. Sequencing remains governed by ZPDES [8,9], preserving structured progression and pedagogical coherence while reducing the cost of expanding expert-quality content. At the micro level, a constrained generative module intervenes during exercise resolution in well-defined situations, such as persistent difficulty despite pre-generated support or open-ended tasks requiring analysis of learner-produced text. In these cases, targeted real-time hints or feedback can be produced under strict pedagogical constraints to ensure

[5] `https://blogs.worldbank.org/en/education/adaptive-learning--a-response-to-cote-d-ivoire-s-educatio`

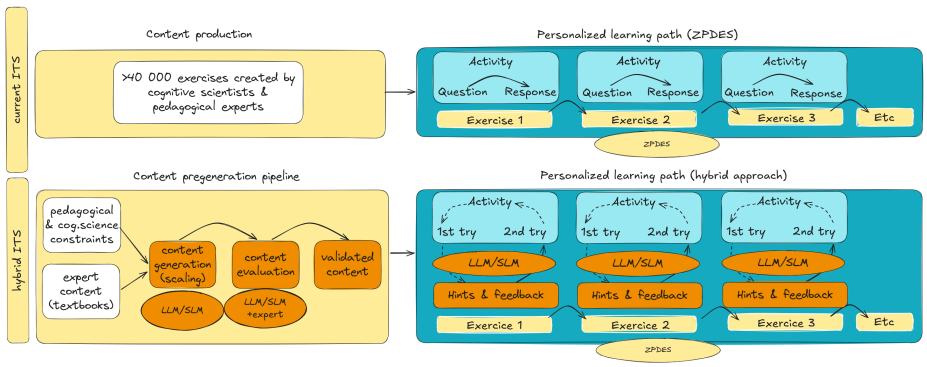

Fig. 2. Personalized learning path: a classical ITS with ZPDES (top), hybrid approach where the ZPDES-based ITS is enriched with generative AI functionalities: pre-generation of content and within-exercice guidance and feedback (bottom)

consistency with the instructional logic embedded in the ITS, with a long-term objective of relying on task-specific SLMs for improved frugality and deployment robustness. This architectural separation allows most generative processes to occur offline (content pregeneration and validation), thereby limiting uncontrolled real-time generation, while preserving the capacity for fine-grained adaptation when pedagogically justified.

2 Reflection on the Challenges and Opportunities Associated with Implementation

Generative AI fulfills two complementary roles within GAIMHE: (1) large-scale pregeneration of pedagogical content and (2) adaptive, within-exercise guidance.

2.1 Implementation Goals and Challenges

Pregeneration of Pedagogical Content We leverage LLMs to generate exercises and structured feedback at scale under explicit pedagogical specifications. Alignment with curricular objectives is supported by relying on open-access textbooks (Manuels Libres IDF[6]) as reference corpora. These materials are structured as graphs to ensure architectural compatibility, define explicit pedagogical constraints per exercise type, and guide the LLM toward coherent outputs.

A primary challenge is ensuring alignment with established instructional and cognitive science principles. Because generative models are not inherently theory-driven, pedagogical constraints must be formalized and systematically verified. Human expertise therefore remains central, particularly during early development and calibration phases.

[6] https://lesmanuelslibres.region-academique-idf.fr/

A second challenge is balancing scalability and quality assurance. Manual validation ensures rigor but limits scale, whereas full automation risks subtle misalignment. We address this tension through an LLM-as-judge approach [7], in which a separate model pre-filters outputs against predefined pedagogical criteria before expert review. Its efficiency depends on calibration against structured human annotations, which both validate generated content and provide supervision signals to iteratively align the LLM-as-judge with expert standards, progressively strengthening rigor and scalability.

Environmental cost constitutes an additional constraint. Large-scale generation with high-capacity LLMs is computationally intensive. We therefore aim to develop task-specific small language models (SLMs) fine-tuned on pedagogically annotated corpora, offering improved sustainability while preserving instructional alignment.

Online Within-Exercise Guidance and Feedback The second role of generative AI involves real-time adaptive hints and feedback. Current feedback remains largely generic, whereas research highlights the central role of error-contingent guidance in learning [10,31]. Our objective is therefore to generate feedback aligned with learners' error patterns and evolving trajectories. Real-time support is particularly relevant when students persist in difficulty despite pre-generated hints or when tasks involve open-ended responses. In such cases, LLMs can produce targeted guidance grounded in learner input.

However, general-purpose LLMs may reveal solutions prematurely or deviate from instructional logic. We therefore constrain generation to level-adapted, stepwise hints consistent with scaffolding principles [23]. Progressive guidance may adopt a conversational format while preserving productive cognitive effort.

Development follows an iterative pipeline: calibration with simulated learners, expert evaluation, refinement, and eventual training of task-specific SLMs on annotated corpora. Model specialization and reduced size are expected to enhance robustness, controllability, and sustainability.

2.2 Evaluation of AI Techniques, Learning and Motivational Impact

Generated exercises undergo structured evaluation. Items are first pre-filtered using an LLM-as-judge [7], then reviewed by human experts using a detailed codebook assessing clarity, difficulty, correctness, pedagogical relevance, contextual plausibility, distractor quality, and alignment with the exercise model. Annotators also estimate correction time (<1 minute vs. >1 minute) to inform revision versus regeneration decisions.

Validated exercises proceed to feedback evaluation (clarity, sufficiency, correctness, pedagogical alignment). Each item is reviewed by at least three annotators to compute inter-annotator agreement [7], both human–human and human–LLM-as-judge.

Annotations serve to identify systematic weaknesses, supervise SLM training, and calibrate the LLM-as-judge for semi-automated filtering.

Educational impact is assessed through classroom deployment and a randomized controlled trial (RCT), following methodologies similar to [24,25]. Outcomes include learning gains, competence progression, persistence, and motivation. Dedicated data science and visualization tools support fine-grained analyses of trajectories, error patterns, and interaction dynamics.

This multi-level framework ensures the evaluation of both generative performance and real-world pedagogical and motivational effects.

2.3 Open-source and open-science approach to stimulate the AIED community

Progress in AIED depends not only on algorithmic innovation but also on the field's capacity to ensure reproducibility, verification, and extension of prior work. However, publicly available educational datasets remain limited and unevenly distributed across subjects and contexts, with insufficient metadata standardization and long-term accessibility [30]. These shortcomings constrain replication and cross-study comparison.

At the same time, privacy and ethical constraints complicate the large-scale sharing of fine-grained classroom data, particularly when linked to sensitive student information. This situation calls for carefully designed data releases, privacy-preserving methods, transparent documentation, and explicit data-use agreements [3]. Given that educational AI systems directly affect learning environments and potentially inform policy, they carry a strong obligation to ensure auditability and reproducibility [27].

Moreover, datasets are most valuable when accompanied by standardized formats, executable pipelines, and reusable evaluation tools [32,19]. Indeed, data alone are insufficient if protocols and configurations remain undocumented.

To address these challenges, GAIMHE adopts an open-science strategy that shares aligned datasets, tooling, and documentation derived from its industrial generation-and-validation workflow. This approach aims to enable independent verification, comparative evaluation, and extension across domains, grade levels, and languages, thereby strengthening methodological rigor and promoting transparency as a standard practice in AIED.

2.4 Challenges related to industrial implementation

A key challenge in industrial deployment lies in reconciling research rigor with production constraints, ensuring that scientific advances translate into reliable and usable tools without compromising validity or user experience. Integrating AI-generated hints into an existing ITS architecture requires maintaining system fluidity and efficiency while introducing adaptive functionalities to avoid cognitive overload or performance degradation. These constraints are addressed through structured engineering processes, cross-functional collaboration between research and product teams, iterative classroom testing, and sustained training and pedagogical support to ensure inclusive and responsible adoption.

3 Next steps

3.1 Research Validation and Scalability

To validate the effectiveness of our AI-powered hint generation system, we plan to conduct randomized controlled trials (RCTs) in authentic classroom settings. This will require recruiting participating classes and engaging teachers who understand both the pedagogical value of the system and the associated experimental protocols. A critical component of this phase will be the recruitment and training of expert annotators who are aligned with our research objectives and committed to rigorous data evaluation procedures. Beyond validation, we aim to develop more generalizable models and modular pipelines that can be adapted to other educational domains and datasets, thereby enhancing the scalability and transferability of our approach.

3.2 Ecosystem Development and Long-term Vision

Successful deployment depends on building a sustainable support ecosystem. Our collaboration with multiple stakeholders—including partners supporting teacher engagement (Café Pédadogique[7]), data management and customer relations (Région Île-de-France), infrastructure deployment and integration (Scaleway), and post-deployment mediation and specialized training (ClassCode)—will ensure robust implementation and operational continuity. We will produce comprehensive documentation tailored to both scientific and pedagogical communities and establish teacher training programs covering practical tool usage as well as foundational AI literacy. In parallel, we will continue fostering a community of teachers and researchers to facilitate knowledge exchange and continuous improvement, notably through events such as "Conférence Terrains Innovants."

3.3 Expanding the AI Agent Roadmap

The GAIMHE project has catalyzed the development of an expanded agent roadmap. We envision two complementary AI agents. The first is a companion agent that extends beyond individual exercises to personalize learning trajectories based on student profiles and objectives. It would intervene during motivational challenges or learning impasses, empowering students to become active agents in shaping their educational pathways. The second is a specialized teacher-support agent that analyzes student data and generates natural-language reports, identifies recurring error patterns, and proposes actionable pedagogical interventions. Together, these agents embody our transition from isolated tools to fully integrated AI teammates in education, strengthening both learner autonomy and teacher effectiveness at scale. To further advance this roadmap, we actively seek academic collaborators interested in learner modeling, adaptive systems, human–AI interaction, and large-scale classroom evaluation, with the goal of jointly developing and rigorously assessing next-generation educational AI agents.

[7] https://www.cafepedagogique.net/

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