A Call for Fully Open and Trustworthy Generative AI for Education

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Abstract

The rapid integration of generative artificial intelligence (GenAI), particularly large language models (LLMs), is significantly transforming educational practices, impacting diverse areas from intelligent tutoring to curriculum design and assessment. Current GenAI applications in education predominantly rely on closed-source, commercial models, raising critical concerns related to transparency, data privacy, interpretability, and trustworthiness. In contrast, open-source models like LLaMA and DeepSeek-R1 offer enhanced transparency and foster community-driven development, yet remain underutilized in educational research and applications. This position paper argues for **a strategic shift toward fully open-source and trustworthy GenAI in education**. We highlight the benefits of transparency, reproducibility, equitable accessibility, and auditability provided by open-source solutions, address practical considerations and challenges, and propose actionable recommendations and policy initiatives to encourage collaborative development among educators, researchers, and policymakers.

1 Introduction

Recent years have witnessed the rapid emergence of powerful generative artificial intelligence (GenAI), including visual generative models (e.g., Imagen [1], Parti [2], DALL-E [3, 4], and Stable Diffusion [5]), large language models (LLMs) such as GPT-series [6], Gemini [7], LLaMA [8], and DeepSeek [9], and multi-modal large language models (MLLMs) including LLaVA [10], BLIP-2 [11], and GPT-4o [12]. Among these, LLMs have demonstrated particularly impressive capabilities, including understanding textual context, processing complex prompts, reasoning over information, and generating highly coherent, contextually relevant textual outputs [13, 14].

The rapid development of these powerful LLM models has led to widespread adoption across numerous domains, from healthcare [15, 16, 17], finance [18, 19], scientific discoveries [20, 21, 22], transportation [23, 24, 25], up to education [26, 27], etc. In particular, education has significantly benefited from the integration of GenAI technologies, driven by their potential to fundamentally transform teaching methodologies, curriculum design, student learning and educational research [28, 29, 30]. As educators and learners increasingly embrace GenAI models, GenAI promises transformative potential by delivering personalized, scalable, and interactive learning experiences, fundamentally reshaping both educational content delivery and accessibility.

Status Quo. Since 2023, academic research has highlighted the increasing prominence of GenAI applications across diverse educational scenarios. Recent literature identifies several primary use-cases. (1) **As a tutor/assistant**: In designing an intelligent tutoring system, tips from the system or virtual tutors are crucial in helping students solve difficult questions in disciplines like mathematics. Traditionally, the manual design of general tips by teachers is time-consuming and error-prone [31], while generative AI like ChatGPT [6] presents a new channel for designing general tips [32, 33].

Submitted to 39th Conference on Neural Information Processing Systems (NeurIPS 2025). Do not distribute.

(2) **For curriculum development**: The results of research of determining whether students' math achievements improved using ChatGPT to prepare lesson plans in primary school math courses is effective in academic achievement [34]. Teachers should consider ChatGPT and their plans, combining them and benefiting from both in the implementation process [35, 36]. (3) **For enhancing student achievement**: One investigation examines the influence of ChatGPT on mathematics achievement, with a specific focus on the moderating role of students' interest in mathematics [37]. Recent studies identified a statistically significant positive moderation effect of students' interest on the association between ChatGPT usage and mathematics achievement [38, 39]. (4) **For model development**: A lightweight expression-enhanced large-scale pre-trained language model, called EBERT [40], for mathematics education. Through downstream tasks in mathematical education, models like this can outperform several former state-of-the-art baselines (such as MathBERT [41] and GPT-3 [42]) in terms of accuracy and F1-score [43, 44]. (5) **Evaluation of GenAI ability**: Recent research explores methodologies aimed at fostering a synergistic relationship between generative AI and human intelligence, encouraging the students' development of robust problem-solving strategies while harnessing the computational capabilities of AI [45, 46, 47].

Motivation. Despite these advancements, critical limitations remain prevalent in the current GenAI-for-education (GenAI4Edu) landscape. Primarily, the sector is heavily dominated by proprietary (closed-source) models such as ChatGPT, developed and controlled by large commercial entities. Although commercial models benefit from centralized resources, rapid iterative cycles, and widespread market penetration, they inherently lack transparency and openness [48, 49]. This opacity introduces significant challenges regarding model *interpretability*, *data privacy*, *equitable accessibility*, intellectual property rights, and accountability in educational contexts [50]. In contrast, open-source GenAI models—such as the LLaMA series and the recently emerged DeepSeek-R1 [9]—provide greater transparency, reproducibility, and community-driven innovation, democratizing access to advanced educational AI tools. Indeed, recent breakthroughs such as DeepSeek-R1 illustrate that open-source alternatives can now match or exceed the performance and capabilities of commercial models [9]. However, our comprehensive review of recent educational GenAI literature (detailed in Sec. 2) reveals that, in the experimental studies, approximately 73.8% of closed source compared to only 7.4% employing open-source in education field(See Figure 1). Furthermore, substantially fewer research initiatives have pursued the development of specialized, education-centric open-source GenAI models, with even fewer openly releasing their models, code-bases, or data, highlighting a critical gap and missed opportunity within the educational research community [51].

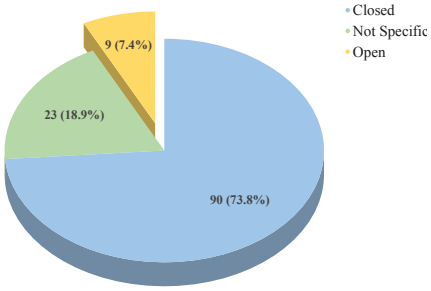


Figure 1: Percentage of Open vs. Closed-Source LLMs used in Education.

Our Position. In this position paper, **we advocate that future generative AI models and platforms for education should focus more on fully open-source and trustworthy resources.** We argue that adopting fully open-source GenAI will enhance transparency, encourage equitable access, and significantly improve accountability, addressing many existing challenges faced by proprietary solutions. Open-source GenAI fosters extensive collaboration, accelerating innovation, community engagement, reproducibility, and rigorous auditing—critical components for achieving trustworthiness in educational settings. In the following sections, we first provide a comprehensive review of prior works relevant to GenAI for education in Sec. 2, then present our position that open-source GenAI platform for education is promising in Sec. 3. We have presented our initial explorations of such an open source platform in Sec. 4, while Sec. 5 discuss possible counterarguments and address potential limitations of our proposed approach. Finally, we conclude with actionable recommendations and policy proposals for educators, researchers, AI developers, and policymakers in Sec. 6, aiming to catalyze a shift toward open and trustworthy GenAI in education.

2 A Review of Prior Works

Generative AI for Education. We conducted a systematic and comprehensive review of recent literature on GenAI and LLMs in educational contexts, following a structured methodology adapted

from established guidelines outlined by Chandler et al. [52]. Our review encompasses a total of 210 peer-reviewed articles published in English from 2023 to May 2025, comprising 54 review articles and 122 experimental studies. These articles were identified using targeted keyword searches (i.e., "LLM in education" and "GenAI education"), followed by rigorous screening and duplicate removal.

Our analysis indicates that, among the 122 experimental studies, only nine explicitly utilize fully open-source models [31, 40, 44, 53, 54, 55, 56, 57, 58] (see Figure 1). The predominance of closed-source, commercial GenAI models underscores a significant reliance on proprietary technologies such as ChatGPT, Gemini, and DeepSeek [9], which are predominantly developed in technologically advanced nations including the United States, the United Kingdom, and China (see Figure 2). This geographic concentration of GenAI research and development creates barriers for researchers and educators from lower- and middle-income countries, who often face limited access to costly commercial models and proprietary resources. Consequently, such disparities exacerbate global inequities in educational innovation and access to advanced educational technologies.

Open-Source vs. Closed-Source LLMs. Existing LLMs can be categorized based on their openness into three primary types (see Figure 3): (1) **Closed-source (proprietary)** models, which are developed by commercial entities and restrict public access to their architectures, training data, and internal parameters; (2) **Open-weight** models, where trained model parameters (weights) are publicly available but the training code or data remains inaccessible; (3) **Fully open-source** models, characterized by publicly accessible architectures, training scripts, datasets, and model parameters; and (4) **Open-development** models whose contributable process is also shared.

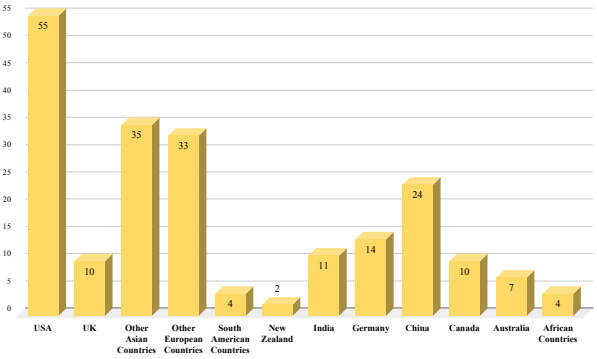


Figure 2: Geographical locations of the published papers.

Closed-source models, exemplified by GPT-4 [12] and Gemini 1.5 [59], offer advanced capabilities and rapid development cycles facilitated by significant commercial resources. However, their proprietary nature inherently restricts transparency, limits interpretability, and complicates customization for specialized educational needs. These "black-box" limitations pose substantial challenges for educational stakeholders in terms of ethical accountability, data privacy, fairness, and equity.

Furthermore, the reliance on closed-source GenAI introduces significant economic and operational barriers for educational institutions in resource-constrained regions, restricting their ability to fully harness the benefits of advanced AI tools. Proprietary licensing and costly access fees often exclude educators in developing nations, perpetuating educational disparities. Moreover, the lack of transparency inherent in closed-source models complicates thorough assessments of model reliability, bias, and fairness, critical factors in educational settings.

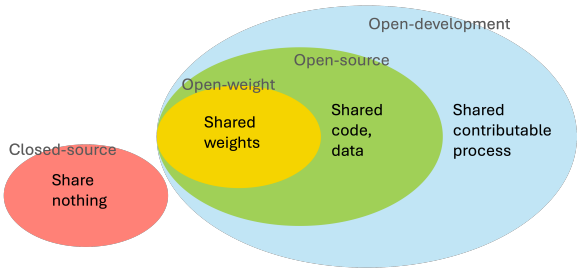


Figure 3: Definition of Open-Sourceness.

Given these challenges, a strategic pivot toward fully open-source GenAI models is necessary to democratize access, foster transparency, and enable rigorous community-driven improvements. We posit that transitioning to open-source frameworks is not only ethically prudent but also essential for equitable and sustainable educational innovation globally. In the subsequent section, we articulate our detailed position advocating for a fully open-source and trustworthy GenAI approach to education, outlining practical pathways and addressing anticipated challenges.

3 Position

As discussed in Sec. 1, the prevailing dominance of closed-source, proprietary GenAI models significantly limits transparency, equity, and accountability in educational applications. To this end, we propose a fundamental shift towards the development and adoption of fully open-source GenAI models explicitly tailored for educational purposes.

3.1 Why Focus on Open-Source GenAI for Education?

We argue for a strategic emphasis on open-source GenAI based on four critical dimensions:

Reproducibility (Data, Model, and Training). Reproducibility is essential for advancing scientific knowledge and validating educational methodologies. Open-source GenAI enables researchers and educators worldwide to reproduce experiments, verify results, and build upon prior work effectively. With unrestricted access to data, training scripts, and model checkpoints, the educational community can rigorously assess model robustness and performance across diverse learning contexts, thus promoting consistency and reliability in educational AI deployments [60].

Accessibility (Economic Equity and Equitable Resource Distribution). The economic disparities between developed and developing regions often restrict equitable access to proprietary AI technologies, exacerbating existing educational inequalities [61]. Fully open-source models mitigate these financial barriers by eliminating licensing fees and enabling cost-effective implementation, thereby ensuring wider, equitable participation. Particularly for rural and economically disadvantaged areas, open-source solutions can facilitate significant improvements in educational quality and accessibility, leveling the playing field for underrepresented communities.

Transparency and Interpretability. Educational settings require a high degree of transparency and interpretability, ensuring that AI-driven educational tools are ethically aligned, unbiased, and comprehensible [62]. Unlike closed-source solutions that operate as opaque "black boxes", open-source GenAI models provide transparent insights into their architecture and decision-making processes [63]. This transparency enables educators, learners, and stakeholders to better understand and address potential biases, promoting fairness and enhancing the ethical deployment of AI in education.

Trustworthiness (Safety, Security, and Privacy). Trust is fundamental in educational contexts, requiring AI systems to be safe, secure, and respectful of privacy [64]. Open-source models offer distinct advantages in terms of security and privacy by allowing comprehensive audits and community-driven security enhancements [65]. Stakeholders can collaboratively identify vulnerabilities, promptly rectify security issues, and enforce rigorous privacy protections. Consequently, open-source GenAI fosters a more secure and trusted educational environment, safeguarding students' data and ensuring ethical AI use.

In summary, embracing fully open-source GenAI models for education not only addresses critical limitations posed by proprietary systems but also fosters an equitable, transparent, and trustworthy educational landscape. The subsequent sections detail practical considerations, potential challenges, and actionable recommendations to realize this strategic shift.

3.2 Preparedness for Open-Source GenAI Platforms for Education

In this subsection, we evaluate the feasibility and infrastructure readiness for developing an open-source GenAI platform powered by LLMs specifically for educational purposes.

Existing Open-Source LLMs. The Meta LLaMA series (e.g., LLaMA 3 [8]), InternVL [66, 67], and Mistral [68] are all prominent open-source LLMs. The maturity, adaptability, and inherent openness of such open-source models enable the necessary domain-specific fine-tuning that would be difficult with closed-source alternatives. Meta's LLaMA 3 family [8] includes pre-trained and instruction-tuned generative text models, available in various parameter sizes (e.g., 8B, 70B), optimized for dialogue use cases. InternVL [66, 67], particularly InternVL3-78B [69], is one of the state-of-the-art multimodal LLMs (MLLMs) that integrate visual and linguistic capabilities during a unified pre-training stage. Mistral [68], including models like Mistral 7B and Mistral-8x22B, is another notable open-source LLM, often leveraging a sparse Mixture-of-Experts (SMoE) architecture. The transparency and flexibility inherent in these open-source models are crucial for research, development, and customization, especially for domain-specific fine-tuning in areas like education.

Educational Dataset Availability. Recently, researchers have made efforts in significantly expanding educational datasets across various learning domains, thus providing abundant data for fine-tuning open-source LLMs to enhance their efficacy in educational applications. Taking mathematics as a specific example, relevant teaching data may include following datasets. (1) **StudyChat Dataset**: a publicly available resource designed to understand real-world student interactions with an LLM-powered tutoring chat-bot, comprising conversations and student utterances [70]; (2) **Multi-turn Classroom Dialogue Dataset**: a benchmark for assessing student performance in math questions based on teacher-student dialogue data from online one-on-one tutoring classes [71]; (3) **MathDial Dataset**: a specialized dialogue tutoring dataset focused on math reasoning problems and common student confusions, richly annotated with GPT-3.5 simulated student confusions and pedagogical attributes [72]; (4) **Education Dialogue Dataset**: a novel multi-turn dataset simulating dynamic teacher-student interactions, entirely generated by prompting Gemini Ultra [73].

Cost-Effective Cloud GPU Platform. Training and fine-tuning large language models necessitate substantial computational resources, particularly high-end Graphics Processing Units (GPUs) with significant memory. While traditional cloud service providers such as AWS, Google Cloud, or Azure often entail considerable expense, several cost-effective GPU cloud platforms currently offer competitive rates for rental services, making previously unattainable projects financially viable for smaller teams and academic researchers with limited resources.

Application Deployment Infrastructure. The deployment and operationalization of GenAI educational tools are now supported by a wide range of robust platforms such as Vercel, Render, and Netlify. These services facilitate seamless backend integration, rapid prototyping, and scalable deployment of interactive learning systems, enabling educators and developers to bring AI-powered tools directly to classrooms and learners.

School and Societal Preparedness. We also assess the preparedness of educational stakeholders [74] and the broader societal context, encompassing ethical considerations, data privacy, and public perception. While initial perceptions of AI in education among teachers and the public may have been characterized by apprehension and a focus on risks such as cheating or declined creativeness [75], recent trends indicate a growing recognition of AI's positive potential, and a notable shift towards greater awareness, acceptance, and proactive integration of AI technologies within educational settings [76]. Many forward-thinking schools move beyond initial hesitation to actively explore and implement AI application to education and integrating tools into their teaching practice [77]. Although GenAI has brought challenges, a vast majority of students report using AI technologies in their academic activities [78], among which virtual assistants and AI-based educational platforms are particularly popular. Additionally, despite concerns about data collection and misinformation [79], nowadays parents generally exhibit cautious optimism regarding the integration of AI in schools. They acknowledge GenAI's potential benefits in education and remain optimistic about using GenAI in academic assistance and research.

Taken together, these developments affirm the technical and institutional feasibility of building open-source GenAI platforms for education. With access to state-of-the-art models, curated domain-specific datasets, affordable compute infrastructure, and a receptive user base, the necessary components are already in place. This preparedness paves the way for scalable, equitable, and trustworthy AI integration in education, reinforcing the urgency and viability of the open-source agenda advanced in this paper.

3.3 Roadmap to Implementing a Fully Open-Source GenAI Platform

Realizing a fully open-source GenAI platform for education requires coordinated, interdisciplinary action across multiple domains of expertise. This section outlines practical steps and roles for education researchers, computer scientists, and institutional stakeholders to co-develop a trustworthy, scalable, and pedagogically sound AI system.

Interdisciplinary Collaboration and Joint Development. Effective deployment begins with building sustained partnerships between technical and educational communities. We advocate for the formation of cross-disciplinary working groups comprising computer scientists, AI engineers, education researchers, and practicing educators. These teams should engage in joint model design, dataset curation, iterative testing, and pedagogical alignment. Formal structures—such as collaborative

research grants, co-development labs, and recurring workshops or summits—can institutionalize this collaboration and ensure ongoing feedback exchange [80].

Responsibilities of Key Stakeholders. *Education researchers* are responsible for defining pedagogical use cases, identifying key learning objectives, and collecting representative data from real classroom contexts. Their work includes annotating instructional dialogue, modeling student misconceptions, and empirically evaluating system efficacy through classroom trials [80]. *Computer scientists and engineers* will lead the development, fine-tuning, and deployment of open-source LLMs [81]. Their responsibilities include selecting appropriate architectures, implementing scalable training and serving pipelines, and ensuring system robustness, efficiency, and privacy compliance [81]. Together, these communities must co-design interfaces and feedback mechanisms to support teacher-facing and learner-facing applications [82].

Technical Infrastructure. The platform must be supported by robust AI infrastructure [81]. Training should be distributed across open-weight models (e.g., LLaMA, Mistral, DeepSeek-R1), leveraging cost-effective GPU resources and academic compute clusters. Model serving must include modular deployment pipelines, enabling localized adaptation, multilingual support, and continuous monitoring. Tooling for model versioning, reproducibility, and bias auditing should be integrated from the outset.

Deployment and Maintenance. Beyond development, serving the model to educators and students requires intuitive interfaces and accessible deployment solutions [82, 83]. Cloud-based backends (e.g., Render, HuggingFace Spaces) should be leveraged to provide browser-based, low-latency access. Open APIs must be maintained to support plug-and-play integration with existing learning management systems and teacher platforms. Continuous updates, community documentation, and open governance are essential for sustainability.

Building a fully open-source GenAI platform for education is technically feasible and institutionally necessary—but it will not succeed without deliberate, collaborative, and inclusive development. This roadmap calls on both the machine learning and education communities to jointly invest in shared infrastructure, open standards, and empirical best practices. Only through such collective effort can we ensure that the future of educational AI is transparent, equitable, and aligned with public interest.

3.4 Key Considerations for Developing a GenAI Platform

In designing and deploying a GenAI platform for education, several foundational principles must guide development. These considerations not only ensure technical and pedagogical soundness but also underscore why open-source models are better suited for building responsible, equitable, and sustainable AI systems in education.

Reproducibility. Reproducibility is a cornerstone of academic integrity and scientific progress. In education, where empirical validation is essential, researchers must be able to replicate results, scrutinize model behavior, and extend prior work with confidence. Open-source LLMs provide access to training code, datasets, and model checkpoints, enabling rigorous peer review and longitudinal evaluation. By contrast, closed-source models obstruct this process, limiting transparency and hindering the accumulation of shared knowledge across institutions and contexts [51].

Accessibility. Widening access to advanced GenAI tools is imperative for reducing educational inequality. Open-source models typically eliminate licensing fees and reduce the financial burden on under-resourced institutions and educators. In addition, open platforms should be paired with user-friendly interfaces, multilingual capabilities, and clear documentation to minimize technical barriers to entry. This lowers the threshold for adoption in diverse educational settings, particularly in underserved or rural communities that are most in need of scalable and affordable AI support.

Transparency. Transparent and interpretable AI is critical for ensuring ethical, fair, and inclusive educational outcomes. Unlike proprietary models, which obscure internal mechanisms, open-source systems allow educators and researchers to inspect how models are trained and how decisions are made. This is especially important in high-stakes environments like education, where algorithmic opacity can perpetuate biases or undermine trust. Open systems empower multidisciplinary oversight—engaging ethicists, educators, and policy makers in assessing fairness, interpretability, and accountability across student populations [84, 85, 86, 87].

Trustworthiness. Establishing trust is foundational when integrating GenAI into educational environments [88, 89]. Trustworthiness in this context encompasses a multi-dimensional evaluation

that includes factual accuracy, safety against adversarial manipulation, robustness to unseen conditions, preservation of privacy, and fairness in the treatment of diverse user groups [90]. These dimensions—thoroughly outlined in the AutoTrust benchmark —are equally critical when deploying GenAI in classrooms, where students and educators rely on AI not only for accurate content but also for safe, ethical, and equitable interactions.

Factuality and Uncertainty Awareness. Just as in autonomous driving systems, educational GenAI must avoid hallucinations or misleading content [91, 92]. Models should not only provide accurate answers but also signal uncertainty when relevant. This helps prevent overconfident misinformation—a critical requirement in high-stakes learning contexts. Open-source frameworks offer the necessary transparency to audit and refine these behaviors systematically.

Safety and Adversarial Robustness. GenAI platforms for education are susceptible to misuse, such as adversarial prompts that induce inappropriate or off-topic responses. Drawing lessons from adversarial testing in vision-language models (VLMs) for autonomous systems [90], developers of educational GenAI must implement safeguards against both benign errors and malicious manipulations. Open-source development facilitates community-driven discovery and mitigation of such vulnerabilities, a process hindered in proprietary systems.

Privacy Preservation. As educational GenAI systems interact with sensitive student data (e.g., learning disabilities, behavioral feedback), they must actively protect privacy and avoid unintended leakage. The AutoTrust evaluation shows that even advanced models can be coaxed into revealing private details unless explicitly trained to resist such prompts. Open-source architectures enable institutions to impose custom privacy controls and transparency audits—essential for compliance with student data protection regulations like FERPA [93, 94].

Fairness and Bias Mitigation. AI must treat students equitably across demographic lines [95]. AutoTrust's fairness testing identifies disparities in model behavior depending on user identity or environmental features. Similarly, educational AI must be validated to ensure consistent performance across student populations—regardless of language, socioeconomic status, or learning style. Open models permit targeted bias analysis and correction, allowing stakeholders to collaboratively enforce fairness.

In summary, trustworthiness in educational GenAI is not a monolithic criterion but a composite of verifiability, security, resilience, and ethics. Open-source models offer a uniquely powerful substrate for achieving these goals, as they invite scrutiny, enable adaptation, and promote accountability—attributes that proprietary solutions systematically obscure. By adopting a trustworthiness-first design philosophy, educational institutions can safeguard learners while enhancing the reliability and social value of GenAI systems.

3.5 Incorporating Feedback to Make GenAI-Education Platform Better

To effectively integrate a GenAI platform in education, a practical approach involves iterative improvement based on educator and practitioner feedback. This ensures the platform continuously benefits educators and adapts to their individual needs [96].

The GenAI platform generate diverse professional development training materials with various contexts for instructors and users such as detailed documentation, training videos, user guides, booklets, and an accessible support website [97]. Before full implementation, education experts will pilot-test the platform to provide structured feedback on content accuracy, pedagogical effectiveness, and user experience. The feedback will provide direction about how to adjust and refine the training methods and interface design for the platform. Then, the large-scale trials will expand to partnership universities around the local area and will be conducted by collecting quantitative useful data and qualitative feedback via interviews from various educators to optimize platform scalability and localization features. This input will guide model development, emphasizing local applicability and broader usability. Following regional validation, the system is promoted in progress and can be publicized to broader universities across the US and up to the global education networks. Continuous feedback collection and maintenance are crucial for enhancing the model's practicality and ensuring ethical considerations, including diverse cultural understanding.

Local experts will establish regular review cycles, analyzing user behavior and survey responses to ensure instructional relevance and technological integration get iteratively improved.

4 Our Pilot Study

Our team has made initial progress in the development of an innovative and fully open-source educational GenAI platform, training and deployment of which are both transparent. It is designed to employ an LLM to simulate responses from a student struggling with mathematics, thus enabling interaction between prospective secondary mathematics teachers (PSMTs) and simulated students. Our basic user interface (UI) design and major features are showcased below (See Figure 4).

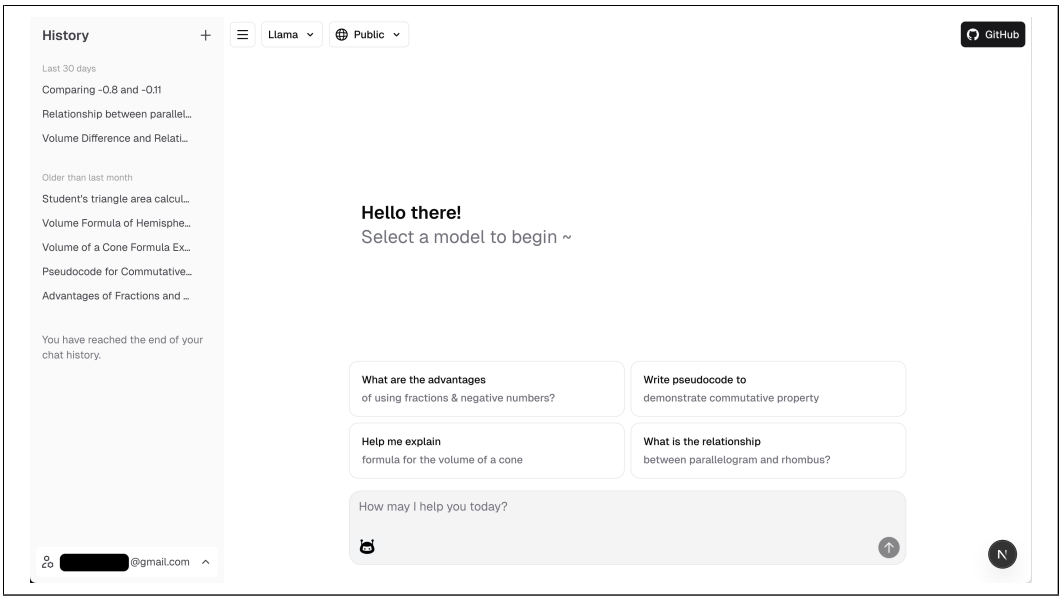
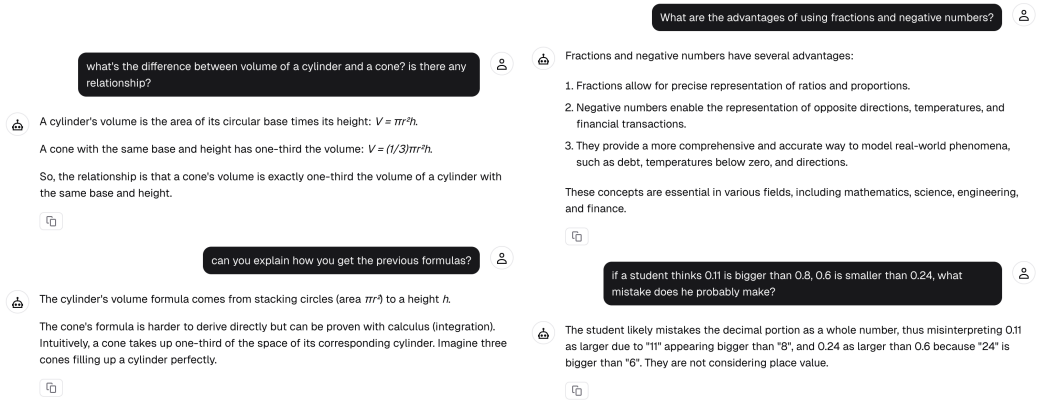


Figure 4: Our User Interface Design



(a) Problem 1 (b) Problem 2

Figure 5: Chat History between Mathematics Teachers and the Chat-Bot

The LLMs, specifically LLaMA 3 model [8] fine-tuned on teaching conversation data from different grade level mathematics classes, are the most essential GenAI component in our platform. Our aim is to eventually develop a chat-bot that can simulate reasonable responses to math problems or teachers' instructions, and contribute to conversations just as a middle school student who is experiencing difficulties in mathematics and stuck in specific questions. Tasked with facilitating and address the queries and inquiries from students in need of mathematics learning help, users (i.e. PSMTs) can effectively practice their teaching skills, identify common student errors and misconceptions, and refine their pedagogical approaches in real-time.

While LLMs' effective mathematics instructional and tutoring ability is still questioned nowadays [98], by casting the GenAI in the role of a student struggling with mathematics, we actually shift the onus of correctness and instructional quality back to the human teacher, navigating its current limitations in consistently providing accurate feedback. Also, to address deficits of the current LLM and decrease the possibility of outputs inconsistent with student roles, we plan to let prospective mathematics teachers and instructors participate in the following testing process and identify cases and situations where the GenAI model fail to generate satisfying responses.

5 Alternative Opinion

While this paper advocates for the development of open-source GenAI platforms in education, we still acknowledge the compelling advantages offered by current closed-source commercial models. It is controversial that, at least at present, existing open-source models may not always match or compete with the performance and convenience of their commercial counterparts [67]. Besides the fact that the key performance indicators of open source models are close to but have not yet exceeded closed-source commercial models, the closed-source (proprietary) models offer several other benefits that contribute to their widespread adoption. (1) **Ease of Use**: Commercial models, such as those from OpenAI [12] and Google [59], are typically offered as managed services accessible through user-friendly web interfaces or well-documented Application Programming Interfaces (APIs). This significantly lowers the technical barrier to entry for educators and developers, allowing for rapid integration and experimentation without deep technical expertise in model deployment or infrastructure management. The convenience is a major draw for many users. (2) **Service Support**: Users of closed-source models generally do not need to undertake the complex and resource-intensive process of model pre-training or extensive fine-tuning. Commercial providers manage the entire life-cycle of their models, including continuous improvement, updates, and maintenance. Professional technical support teams can even provide custom solutions tailored to specific industry (including education) needs, and help schools respond to sudden needs quickly, while the open source community has not yet formed a similar standardized tool chain.

The current commercial model is inevitably the mainstream choice for educational institutions due to its substantial convenience, immediate utility, complete functional chain, and reliability; while it is still undeniable that open source models have great market potential because of better performance in data privacy protection and localized customization, and they will become an indispensable market trend for future educational applications.

6 Conclusion

We call for more open, inclusive, efficient, and trustworthy generative AI applications in education. Fully adopting open-source GenAI can enhance transparency, ensure fair access, and improve accountability—addressing many issues seen in proprietary systems. Open-source models foster collaboration, innovation, reproducibility, and rigorous peer review, all essential for credibility in education. We offer practical suggestions and policy recommendations for educators, researchers, developers, and policymakers, including joint research, co-creation, interdisciplinary events, standard data frameworks, and collaborative human–machine interaction. These strategies can help align AI advancements with effective teaching practices, supporting a more inclusive and impactful educational ecosystem.

Future Directions. Moving forward, we aim to extend our pilot system into a broader ecosystem that supports a range of instructional roles, from AI student simulators to intelligent teaching assistants. Further work is needed to design community-driven benchmarks that evaluate GenAI models for pedagogical soundness, fairness, and robustness in diverse educational settings. To support real-world adoption, we also emphasize the importance of integrating these systems into institutional infrastructures, aligning with educational standards and privacy policies. In parallel, we advocate for participatory governance frameworks that involve educators, researchers, and policy stakeholders in model iteration and oversight. These directions will help realize an educational AI landscape that is not only technically advanced, but also open, inclusive, and grounded in public interest.

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