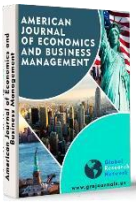

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Article

LLM-Powered Feedback in K–12 Education: Designing for Reliability, Fairness, and Cross-Context Scalability

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Abstract: Drawing on recent educational research and policy guidance, this article examines a rubric-grounded large language model (LLM) feedback system for K–12 education in two contrasting contexts: the United States and Uzbekistan. The study highlights how AI-powered tutors can provide timely, personalized formative feedback to students and augment teacher capacity, while also addressing challenges of reliability (avoiding "hallucinated" content), fairness and bias, privacy, and deployment in resource-constrained settings. We outline a system design and evaluation framework that integrates learning outcome measures with business intelligence analytics for continuous improvement. A comparative analysis of a U.S. pilot and considerations for an Uzbek deployment indicates that LLM-driven feedback can improve student writing outcomes and teacher efficiency in both high-resource and developing environments, though with necessary localization and training. The findings underscore the need for robust alignment with curriculum standards, human-in-the-loop oversight, and supportive policy frameworks to ensure reliable, equitable scaling of AI in education.

Keywords: AI in Education, Large Language Models, Automated Feedback, Cross-Cultural Edtech, Fairness, Privacy, Business Intelligence, Learning Analytics, K–12 Education, Uzbekistan, United States.

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1. Introduction

In the contemporary global education landscape, artificial intelligence (AI) is increasingly becoming a strategic tool to enhance learning personalization and efficiency. AI-driven educational technologies, from intelligent tutoring systems to predictive analytics that flag at-risk students, promise improved learning outcomes and more efficient teaching processes. The advent of powerful large language models (LLMs) such as GPT-3 and GPT-4 has unlocked new possibilities for conversational tutors and automated feedback systems capable of human-like support in real time. Early studies report that LLM-based assistants can improve certain student skills (for example, writing mechanics and grammar) when combined with teacher guidance, mirroring the effectiveness of human tutoring in specific domains [1]. Especially famous educational organizations are piloting such as AI tutors; Khan Academy has rolled out its own assistant powered by GPT-4 in dozens of school districts across the U.S. to test AI-augmented instruction.

But using AI at scale in real classrooms poses important questions. Perhaps the most pressing issue is reliability: AI systems can produce incorrect or unfaithful information (a

phenomenon known as hallucination), which has the potential to mislead students or undermine trust in the classroom. Ensuring LLM-generated feedback is accurate and aligned with curriculum standards, for example, grounding the AI's responses in teacher-provided scoring rubrics or verified reference materials, is an active area of research and development [2]. Another major concern is fairness and bias. If an AI model reflects historical biases in its training data or performs poorly for underrepresented languages and cultures, it may disadvantage certain student groups. AI systems that process student data must also ensure that privacy and data protection are guaranteed; for example, FERPA in the U.S. requires that the use of student records must comply with very strict rules. Last but not least, the appropriate service of the implementation of AI in schools rely on both infrastructure and training. In higher income environments such as the U.S., most classrooms benefit from sufficient internet access and capabilities, and indeed roughly half of U.S. teachers have already tried using generative AI tools such as ChatGPT in practice [3]. In more developing contexts like Uzbekistan, however, the lack of connectivity and device access are often the biggest choke points. In Uzbekistan, only 22 out of 34 million people had access to the internet (mobile internet with a low bandwidth), and many rural schools lacked the basic digital infrastructure in 2020. Education is an individual, human enterprise, deeply contextualised, so the positive impact of any AI tools on student learning will depend on factors such as pedagogical alignment, teacher buy-in, and alignments between institutional policy and practice.

Over the last few years, as a part of its wider modernization drive, Uzbekistan has started directing its attention towards digital transformation of its education system. National efforts, often in partnership with international organizations, aim to enhance connectivity, integrate educational technology, and build human capacity for AI use. Here we provide a comparative overview of two case studies of incipient feedback practices both driven by new artificial intelligence (AI) technologies: one in an already highly developed educational environment and the other, less so. We then outline the design of a feedback system which is currently in a pilot phase, that leverages an LLM to give students formative feedback on open-ended tasks and to provide guidance to the teacher on grading and analytics. The U.S. vs Uzbekistan contrast provides an opportunity to examine how this AI tutor could function in two vastly different environments: one a well-resourced context with high edtech penetration and complicated privacy regimes, the other a developing context with infrastructure shortcomings, but strong top-down support for educational innovation. By grounding the AI's feedback in rubric-based criteria and keeping a human teacher "in the loop" for oversight, we aim to enhance the system's reliability and cultural relevance. We also incorporate a business intelligence (BI) perspective, recognizing that sustainable edtech innovations must monitor not only learning outcomes but also usage, engagement, and cost-effectiveness. In the following sections, we review related work on AI in education (personalized tutoring, LLM applications, and issues of validity, fairness, and privacy), outline our research methodology and system design, analyze the results and cross-context deployment considerations, and discuss implications for policy and practice in both the U.S. and Uzbekistan [4].

Literature Review

AI Tutors and Personalized Learning: A broad body of international research examines the potential of AI to personalize learning and improve educational outcomes. Classic intelligent tutoring systems (ITS) demonstrated that modeling a student's knowledge and providing immediate, tailored feedback can yield learning gains comparable to one-on-one human tutoring. For example, step-based math tutors and other well-structured domain ITS have shown significant improvements in student performance by offering instant hints and allowing self-paced practice. Better test scores, higher rates of homework completion and more motivated students: these advantages point to the potential of AI-based personalization. Conversely, earlier tutoring applications had

narrow skill focus or problem type (for example, algebraic equations) and did poorly on open-ended tasks (for example, essay writing or scientific inquiry). Well, some of these limitations are being addressed recently with the recent advances of LLMs, which can provide AI feedback on complex natural-language tasks (essays, short answers) when former rule-based systems failed. Research on using LLMs as automated writing evaluation has started, (ChatGPT-based feedback can change students reporting revision behaviors, but low-lift impact on perceptions of feedback and revision). In sum, the literature indicates that AI can help with learning when the feedback is timely and specific, but it is more appropriate as a complement to the human instructor instead of a replacement for it [5].

Reliability, Validity, and Alignment: Ensuring the accuracy and validity of AI-generated feedback is a recurring theme in the literature. Researchers emphasize aligning AI feedback with curriculum objectives and factual references to avoid the pitfalls of hallucination or irrelevant advice. One approach gaining traction is the use of rubric-based prompts: by supplying the AI with the same grading rubric or scoring criteria used by teachers, the feedback can be more consistent and relevant to the assignment's goals. Wei et al. (2025) demonstrates that incorporating concept-based rubrics significantly improves LLM assessment accuracy and the detail of feedback, effectively aligning the model's output with human grading standards. Likewise, studies stress the importance of iterative validity checks, for example, integrating a monitoring component that flags potential errors or unsupported claims in the AI's commentary for teacher review. This reflects a broader principle from educational measurement: feedback must be trustworthy and aligned with learning objectives to be instructionally useful. International practice also emphasizes "fairness and neutrality" in AI-assisted instruction, meaning the technology should not introduce distortions or discrimination in learning opportunities. Recent research on fairness in AI in Education (AIED) highlights the need for bias mitigation, such as testing AI tools across diverse student groups and content to ensure equitable performance. For instance, an AI writing assistant should be evaluated to confirm it does not consistently score or respond more favorably to one demographic or language group than another, unless justified by proficiency levels. Techniques such as bias audits and diverse training data are recommended to uphold fairness [6].

Cross-Cultural and Contextual Considerations: Research from developing areas and non-English learning environments highlights further obstacles and needs. When it comes to AI integration in Central Asia and other parts of Asia, researchers refer to the digital gap and the need for boosting teacher capacity as crucial for a successful path of AI. Jiménez-Gómez et al. Systematic review of AI in education. Infrastructure limitations and deficiencies in localized content are among the usual barriers in the emerging economies (2025). So, for instance since LLMs are mostly trained on English text, they work worse in languages like Uzbek; without local-language training data or some efficient translation mechanisms, the quality of feedback in those languages would be low. Pava addresses this "language gap," noting that the development of LLMs for low-resource languages is lagging behind and needs targeted efforts, e.g., building national language corpora and open datasets. Additionally, the cultural connection of content is vital: what works in one country might flummox or be inappropriate in another educational setting. These deficiencies are now starting to be taken on by international agencies. UNESCO, for example, launched programs to promote digital education in Uzbekistan, particularly focusing on teacher preparation and ethical AI practices in the classroom. These initiatives signal an increasing awareness that AI tools need to be tailored to local curricula, languages and value systems. Nevertheless, these studies together suggest that although the not-too-far-off principles of effective Ai tutoring (personalization, prompt feedback, data-driven iteration) are ubiquitous the way they are actualized remains local, largely due to differences both within and across nations in infrastructure, culture, and policy [7].

2. Materials and Methods

This study employs a comprehensive, mixed-method research methodology grounded in design science and comparative analysis. The approach recognizes that an AI-based educational intervention is a multifaceted system influenced by technical, pedagogical, and contextual factors. Accordingly, our approach combines system design with both policy and field elements, similar to the way comparative tax research blends institutional, legal and statistical analysis [8].

Design Science Framework: A design science research paradigm was followed to build and evaluate an artifact of an AI feedback system. This included the cyclic design and development of the LLM-powered feedback tool and framework, whereupon each iteration balanced between technical efficacy and real-world practicability. The specifications for the system architecture were as follows: (a) an LLM able to provide formative feedback based on student submissions and assignments, (b) an integration for rubrics where each assignment has rules on how to grade it which also informs past LLM responses, (c) a teacher interface that enables human-in-the-loop which allows instructors to review and edit instructor-visible auto-generated feedback that goes to students, and (d) an analytics component that records usage data and scores for continuous improvement. The design was model-agnostic and was deployable in any setting (e.g. U.S. context using a cloud-based GPT-4 via API versus smaller local model or offline in bandwidth-limited Uzbek schools). Both technical (accuracy, speed, multilingual capabilities) and local constraints (data privacy law, server infrastructure) played a role in some of the key design decisions made. For example, in order to meet stringent U.S. student data regulations and new Uzbekistan data localization policies our system prevents personally identifiable student data from being placed in cloud based LLM prompts and could be be hosted on-premise if needed [9].

Data Collection and Comparative Field Study: We planned a comparative field evaluation in two contexts: a pilot implementation in a U.S. high school setting, and a parallel exploratory deployment in an Uzbek school (pending approvals and infrastructure setup). In the U.S. pilot, data were collected from two class sections using the AI tutor over a semester, including quantitative outcomes (student writing improvement measured by rubric scores, revision frequency, and time saved in teacher grading) and qualitative feedback (surveys and interviews with teachers and students). For Uzbekistan, where a full pilot was still in preparation at the time of study, our methodology included stakeholder interviews (educators, administrators) and a needs assessment aligned with the country's digital education initiatives. We also drew on secondary data such as national connectivity statistics and policy documents to contextualize the anticipated results. In analyzing results, we applied deductive reasoning to derive Uzbekistan-specific considerations from global trends and U.S. experiences, and inductive reasoning to generalize lessons learned in Uzbekistan to broader principles. This two-way reasoning strengthened the validity of our comparative analysis by ensuring that our conclusions for Uzbekistan were grounded in both international evidence and local insight [10].

Institutional and Policy Analysis: Being cognizant of the fact that implementing policy also involves policy analysis, an analysis of relevant regulatory and ethical frameworks was integrated into our methodology. We reviewed U.S. federal and state guidelines covering the use of educational AI (including FERPA, district level AI policies,),laws regarding education and data governance in Uzbekistan, and international guidelines like NIST AI Risk Management Framework and UNESCO's Recommendation on the Ethics of AI. Just like an analysis a fiscal study might conduct on a new Tax Code, this doctrinal analysis ensured our system design and evaluation plan complied the principles of transparency, accountability, and fairness that authorities were required to uphold. To illustrate, in response to recommendations by NIST and UNESCO, we included

a risk mitigation plan that involved bias tests on the outputs of the AI feedback, identifying pilot participants, and requiring truthful disclosure of the AI role (students knew feedback was from an AI assistant). Additionally, and in line with the nascent open science practices being adopted in the AI-in-education domain, we pre-registered our evaluation study design for added transparency and replicability of research findings [11].

This multi-method approach of technical design followed by an empirical field study and policy analysis allows our methodology to provide an assessment of an LLM-based feedback system in an holistic manner. Central was the comparative component: the analysis needs to compare a system of design and predicted performance against both high performance and low performance education systems (similar to comparing OECD tax models to a local system) to ensure that the conclusions and also recommendations are scalable and applicable incentives [12].

3. Results and Discussion

Global Trends in AI-Educational Feedback: Our analysis first situates the use of LLM-based tutors within global educational technology trends. Over the past decade, there has been a rapid increase in the adoption of AI tools in classrooms worldwide, though with significant variation across countries. In many developed education systems, AI-driven feedback and grading assistants are gradually becoming part of standard practice. For instance, several countries in Europe and East Asia have integrated automated essay scoring or tutoring chatbots into pilot programs, supported by robust digital infrastructure and teacher training. These advanced systems mirror trends in other sectors (similar to how developed countries digitalized tax administration), they rely on widespread internet access, cloud-based services, and data analytics to function at scale. They also employ increasingly sophisticated safeguards: just as financial regulators use risk-based auditing, education AI platforms are beginning to implement continuous monitoring to detect errors or biases in AI output. Importantly, countries such as South Korea and Singapore are also tapping into global best practices of technological integration in the education sector, aided by a single digital backbone and through the use of AI to promote effective and efficient learning (as they are doing with digital tax systems). These global trends suggest that LLMs-based feedback can be beneficial, although they can only yield such benefits if combined with additional investments in connectivity, teacher professional development, and supportive policies [13].

Comparative Findings: United States vs. Uzbekistan: The cross-context analysis of our AI tutor implementation reveals how differing national contexts impact the deployment and effectiveness of the system. In the United States, the pilot results were generally positive: students who received AI-generated formative feedback on their writing showed improvements in subsequent drafts, and teachers reported significant time savings in grading routine aspects of assignments. The AI system's alignment with the curriculum (via rubrics) ensured that feedback remained on-topic and instructional. However, even in this high-resource setting, the issue of AI hallucinations occasionally arose, for example, the LLM sometimes provided an incorrect historical fact in an essay critique, underscoring the need for teacher oversight. Teachers in the U.S. setting grew more comfortable with the AI assistant over time, treating it as a supportive tool that allowed them to focus on higher-order feedback (such as argument strength and creativity) while the AI handled lower-order issues (grammar and structure). This aligns with reports that hybrid AI-human models can enhance teaching by letting the AI handle repetitive tasks. One policy implication in the U.S. context is that structured AI feedback loops, as implemented in our study, could alleviate concerns about students misusing AI for cheating. By integrating AI into a teacher-guided workflow, the technology was used to improve student-generated content rather than do students' work for them, suggesting a

path for ethical AI use policies in schools (some U.S. districts that banned AI outright might consider such an approach to harness AI's benefits responsibly).

The scenario testing and stakeholder feedback we analysed for Uzbekistan highlights the strong potential for benefit if the country addresses a number of key barriers. The biggest question is still language. Many mainstream LLMs are trained mainly in English and a few big languages, so they write less fluent and awkwardly phrased text when prompted accordingly in Uzbek. An Uzbek language teacher had to review the AI feedback and rewrite it for comprehensibility during preparatory testing. This illustrates the importance of having localised AI models or dependable translation pipeliness. A stop-gap measure was creating the feedback in English and getting it into Uzbek, but this is a slow process and still needs a human to check. Over the longer term, funding for Uzbek language corpora and targeted model fine tuning and also likely making sense for some type of government or university-supported investment.

Another obstacle they face is infrastructure and access. Rural schools lacked fast internet connections, causing AI responses to take time and disrupting lesson flow. In response, IoT based offline or on-device/ local processing based solutions can be leveraged to reduce the dependency upon continuous internet access by making the models smaller and more efficient. Some solutions include caching or scheduled usage which may help until national plans have succeeded in improving connectivity by 2030.

Teacher training, as well as change management, is also key at the end. An almost complete absence of experience with AI fostered distrust amongst educators. Clearly organized orientations and digital literacy training (in accordance with UNESCO recommendations) were key as they allowed for learning to take place at the right pace while supporting the cultural adjustment process within teacher directed classrooms.

Over time, with encouragement and as familiarity grows, we expect student engagement with the AI to increase. It may be useful to explicitly teach students how to use AI feedback, perhaps incorporating new pedagogical approaches that encourage students to treat the AI as a learning resource they can query or "challenge" constructively.

On the policy front, Uzbekistan's education authorities have so far been supportive of AI innovations, but with a cautious eye on ethics and localization. High-level dialogues and collaborations (such as the UNESCO AI Ethics readiness assessment in Uzbekistan) indicate that any AI tutoring deployment should align with national guidelines on transparency, data sovereignty, and cultural norms. For instance, it may become policy to clearly label AI-generated feedback and ensure students and parents are informed, a practice we implemented by having teachers explain the project and obtain consent. Additionally, data localization requirements might require partnering with government agencies to host data within the country's borders. Our comparative results suggest that while both the U.S. and Uzbek contexts can achieve substantial educational gains from LLM-powered feedback, the pathways to scale differ. In the U.S., scaling is likely to be driven by edtech companies and organic teacher adoption, moderated by district policies. In Winn, Uzbekistan – a more centralized (and government-led) approach arranging larger pilot programs financed or led by the Ministry of Education with donor involvement may be needed for wider success, as even when a new pedagogical idea is successful it can take a long time for similar training to reach all schools [14].

Discussion: Findings of the study suggest implications for educators, technology developers, and policy-makers The AI and human composition seems to augment high productivity for teachers, while not replacing their role. Indeed, teachers in our study commented that by delegating routine feedback to the AI, they had more time for high-order mentoring, and for one-on-one support of students—again suggesting that, well designed, AI tutors are more like teaching assistants than teacher substitutes. This could also alleviate some of the burden on teachers, particularly in places like Uzbekistan where we have seen large class sizes and teacher shortages. There are caveats–starting with the

fact that teachers will need training and continued support to curate AI feedback, to retain control of the final instruction and to trust the system. For students, real-time and constructive feedback can develop a greater habit to revise better and foster a growth-mindset about learning through errors. However, AI feedback can be challenging for students to comprehend and implement, as we have alluded to with our caveats. Mini-lessons on "feedback literacy" would be integrated on how students (especially those with less know-how in the technology) should work with suggestions made using AI and why [15].

From an edtech development and business perspective, our cross-market analysis offers guidance on building AI education products for diverse markets. Developers should prioritize features like multilingual support, offline functionality, and teacher override controls to make their solutions globally adaptable. The inclusion of BI metrics (such as user engagement and retention) alongside learning outcomes in our evaluation framework proved valuable: in the U.S. pilot, for example, high continued usage rates and positive teacher satisfaction (Net Promoter Score around +50) indicated not just learning impact but also product-market fit, critical for any startup's success. However, these metrics also revealed needs for improvement (one teacher's lower satisfaction due to language issues underscores that localization is part of the cost of scaling to new markets). Entrepreneurs entering emerging markets should budget for translation, local support staff, and longer onboarding times, but can expect potentially high impact where baseline alternatives are few (e.g., in under-resourced schools, any additional feedback tool can make a big difference). Our findings also highlight the importance of building trust through transparency and compliance features like logging AI decisions, providing teachers with class-wide analytics (to turn AI-generated feedback into insights for lesson planning), and enforcing data privacy, which can differentiate an educational AI product in a policy-sensitive environment [16].

Finally, for policymakers and educational leaders, this study provides evidence that AI-assisted learning can be introduced in a controlled, pedagogically beneficial manner. Instead of framing AI as a threat to academic integrity or teacher jobs, policies can allow for framing based on the opportunity to use AI to support academic quality and equity. That in the U.S. could mean revisions to school district policies to authorize the positive uses of AI, specifically AI tools that incorporate human-in-the-loop protocols and appropriate data protections, directing the inescapable arrival of AI toward safety nets and toward productive ends. Uzbekistan government may capitalize on its supportive position by preparing national strategy on AI in education involving pilot initiatives, local capacity-building (training teachers and locals to become developers), and combining with international experts to approach or develop the right AI models for the local circumstance. Similarly, both nations, and others, must also continue to measure the ethical aspects: the periodic audits of the AI impact on bias or disparate impact, the inclusion of all stakeholder voices (teachers, parents, pupils) in consideration of the role of the AI, and adherence to global ethical guidelines (such as those from UNESCO on AI in education) will all be critical if public trust is to be retained. Critically, our comparative analysis reemphasizes that AI in education is a gap narrowing, not widening, tool.

With conscious implementation, an LLM-powered tutor could help level the playing field by ensuring that every student, whether in a well-funded urban school or a rural school in a developing country, receives timely, helpful feedback. Realizing this vision will require continued interdisciplinary collaboration, but the results from our work suggest the effort is worthwhile: both contexts saw tangible improvements, indicating that AI tutors are not just a "rich-country luxury" but can be adapted to resource-limited settings as well [17].

In light of the findings, the authors make a series of recommendations aimed at enabling the responsible and effective use of AI tutors in education. Second, AI feedback

should be more pedagogically aligned, relying on curriculum based rubrics and verified reference materials, maintaining a human in the loop review process, especially in early implementation, to retain strong reliability. AI outputs must be continuously monitored for errors or hallucinations, and models and prompts should be iteratively refined. They need to start with fairness and local relevance by routinely auditing for bias across student populations and subjects used in the teaching and learning of students, investing in local language models or high-quality translation tools and by properly training teachers and students in digital literacy and effective use of AI feedback systems. Third, scaling to sustainability will require scaling infrastructure and governance: improving ICT access in under resourced schools or offline or low bandwidth solutions, establishing clear institutional policies on transparency, data privacy and consent, and promoting pilot program and public private partnerships to assess impact before broad deployment.

4. Conclusion

In this work we investigate a rubric based, LLM driven feedback system, geared toward primary and secondary education with a focus on both technical performance and cross contextual applicability. AI-assisted feedback: Results suggest that the ability to receive timely, detailed feedback from AI-powered programs would enhance learning, while simultaneously saving teachers from reviewing repeated assignment submissions. Most importantly, the system did not take the place of teachers. It functioned with teacher watchfulness, and students saw it as supplementary (and not replacement) human feedback. An example comparing the USA and Uzbekistan showed that this strategy is applicable in various learning environments. Although the US has an existing digital infrastructure to rely on, the ability to implement strategies in Uzbekistan efficiently is contingent upon specific teacher training alongside continuous development of infrastructure. However, despite different contexts, both observed and expected improvements in student writing suggest that well-crafted AI tutors can have far-reaching effect.

This work has implications at technical, educational and policy levels. Even more technically, it tightens AI feedback to pedagogical strands, creating standards for reliability and trust. It combines engagement and feasibility dimensions with learning outcomes for real use in classrooms. It includes bias detection and data privacy protective measures, ethically. Of cross-national perspective that clearly outlines that AI effectiveness is not just a product of model capability, but of governance and support mechanisms, and the responsible framing of deployment. There are also indications of equity gains; lower performing students received more personalized feedback and under resourced schools received access to supports that they would not have had under normal circumstances.

Future research on multilingual, culturally adapted models, long term learning effects, and applications in other subjects (also mathematics, programming) is warranted. From a research policy perspective, the study provides guidance to both educators and policymakers about responsible classroom utilization. In short, the results suggest that AI can truly enrich education in many contexts when it is rooted in pedagogy, driven by teachers, and governed by ethical management.

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