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# Towards Fair and Inclusive AI Education: A Review of Bias in LLM-Based Adaptive Learning Systems

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**Abstract**—Adaptive learning platforms are undergoing a significant transformation with the introduction of large language models (LLMs). These models help personalize instruction by interpreting student inputs, offering feedback, and generating relevant learning materials. While this brings tremendous value to education, it also opens the door to some serious challenges.

One of the main concerns is bias. Because LLMs learn from data collected across the internet, they often absorb and replicate stereotypes or cultural imbalances found in that content. These biases can show up in the feedback students receive or the educational materials generated, particularly disadvantaging those from non-dominant cultures, regions, or language backgrounds. This paper looks closely at how such biases appear in two key areas of adaptive learning: feedback systems and content creation. By analyzing 50 recent research studies, we highlight where the problems lie, how they've been studied, and what solutions are emerging. We found that the way a student writes or the name they use can influence the responses they get from an AI. Some students receive a glow or overly critical feedback, while others may not see themselves reflected in learning examples at all.

We introduce a framework to help make sense of these issues, outlining specific categories of bias and exploring practical ways to reduce them. We also review important datasets and suggest tools for simulating diverse student profiles to test how well LLMs perform across different backgrounds. There's a lot of work ahead if we want AI-powered education to be fair and inclusive. But by bridging the gap between technical development and classroom realities, this paper aims to guide future efforts in building systems that treat all learners equally—regardless of who they are or where they come from.

**Index Terms**—Large Language Models (LLMs), Adaptive Learning, Educational Bias, Automated Feedback, Content Generation, Educational Equity, Bias Mitigation, Generative AI in Education

## I. INTRODUCTION

The rise of generative artificial intelligence (GenAI)—especially large language models (LLMs)—is transforming how educational technology is designed and delivered. These models can analyze student input, provide nuanced feedback, and generate learning content on the fly. Their ability to mimic human-like responses and contextual understanding aligns well with the goals of adaptive learning platforms (Kim et al., 2023 [2]; Tuli et al., 2023 [4]). Whether acting as virtual tutors or creating personalized lesson materials, GenAI tools are already reshaping classroom experiences (Chen et al., 2023 [7]; Rajendran et al., 2023 [10]).

Yet, along with this innovation comes a set of critical concerns. Unlike traditional rule-based systems, LLMs are trained on massive datasets from across the internet that often reflect societal biases. When these biases are carried into educational tools, the consequences can be subtle but far-reaching. Studies show that feedback generated by LLMs may vary depending on how a student writes or the perceived background of the learner (Zhan et al., 2022 [5]; Costello et al., 2024 [8]). Likewise, generated content often centers Western norms and overlooks diverse cultural and regional perspectives (Chen et al., 2023 [7]; Lehmann et al., 2023 [7]). This paper examines two areas where such bias is most likely to appear: (1) automated feedback and assessment, and (2) the generation of educational content. In the case of feedback, we look at how a student's phrasing or inferred identity can influence AI responses (Lin et al., 2023 [5]; Zhang et al., 2024 [10]). For content generation, we consider how variables like race, gender, geography, and language are represented or left out in learning materials (Bee et al., 2023 [15]; Lehmann et al., 2023 [7]). To explore these issues, we review 30 recent studies at the intersection of bias detection in LLMs and their use in educational settings. We evaluated detection methods, mitigation strategies like prompt engineering and fine-tuning, and emerging tools for auditing model behavior (Tuli et al., 2023 [4]; Huan et al., 2023 [3]; Chen et al., 2023 [11]). We also assess the utility of widely used educational datasets such as ASAP, ICNALE, and OpenStax, and introduce a framework for simulating student profiles to test bias under controlled conditions.

Our contributions include: a comprehensive literature review, a new taxonomy of bias types specific to education, and the identification of major gaps in current practices—such as the absence of education-specific bias benchmarks and the lack of fairness audits in deployed systems. Ultimately, this work aims to guide the responsible integration of GenAI into education, ensuring that future adaptive learning platforms are not only smart but also fair and inclusive for all learners.

## II. BACKGROUND

### A. Evolution of Adaptive Learning Platforms

Adaptive learning platforms have evolved significantly from early rule-based systems to data-driven, intelligent technologies. Initially, these platforms used predefined logic to adapt content based on student performance. However, with the rise of machine learning, and now LLMs, they are capable of analyzing patterns in student behavior to deliver personalized learning experiences (AI-enabled Adaptive Learning Systems, 2023 [17]; Taking Adaptive Learning to the Next Level, 2023 [18]).

Modern systems like DreamBox, Knewton, and Carnegie Learning utilize real-time data to tailor instructional content, pacing, and assessments. These platforms are increasingly integrated with GenAI, allowing for dynamic interactions, natural language feedback, and content creation aligned with learners' needs (Bringing Generative AI to Adaptive Learning in Education, 2023 [16]).

### B. Capabilities and Risks of LLMs in Education

LLMs such as OpenAI's GPT or Google's PaLM excel in generating human-like text and understanding context from minimal input. Their adaptability has made them valuable tools in educational settings, enabling tasks like essay grading, personalized tutoring, automated QA, and curriculum design (Generative AI and Its Impact on Personalized Intelligent Tutoring Systems, 2023 [22]; Generative Artificial Intelligence in Education, 2024 [29]).

Despite their utility, LLMs pose unique challenges. Because they are trained on internet-scale data, they can inherit and reproduce biases present in those sources. This is particularly concerning in education, where fairness, accuracy, and inclusivity are foundational. Biases may manifest as inconsistent grading, culturally skewed content, or feedback that favors certain demographics over others (Unveiling Gender Bias in Large Language Models, 2024 [5]; Bias of AI-Generated Content, 2023 [7]).

### C. Integration of GenAI in Educational Environments

The integration of GenAI into adaptive learning environments is still a developing field. Systems now incorporate NLP tools to personalize feedback, tailor learning paths, and automate assessment, but often without standardized protocols to ensure fairness and equity. This gap has prompted growing interest in tools for bias detection and mitigation (FairPy, 2023 [4]; Ask-Before-Detection, 2024 [10]).

To support ethical deployment, educators and developers must collaborate on creating benchmarks, monitoring frameworks, and inclusive datasets. The goal is to ensure these powerful tools benefit all students, not just those whose backgrounds align with dominant data representations. The main applications are the following:

- Feedback generation
- Content Creation
- Tutoring and Grading
- Assessment and Grading.

## III. TAXONOMY OF BIAS IN LLM INTEGRATED ADAPTIVE LEARNING PLATFORMS

In the context of adaptive learning platforms powered by large language models (LLMs), bias can be broadly categorized into two domains: feedback and assessment bias and educational content generation bias. Each category reflects how algorithmic systems may unintentionally disadvantage certain learner groups or distort the educational experience.

Feedback and assessment bias occurs when automated systems generate evaluative responses that are unfair or inconsistent across different learner profiles. Linguistic bias emerges when the system favors particular writing styles or penalizes non-standard expressions, often disadvantaging non-native English speakers. Demographic bias refers to disparities in feedback based on attributes like gender, ethnicity, or geographic origin.

Knowledge representation bias rewards responses that align with Western academic norms while penalizing diverse reasoning styles. In terms of interaction patterns, behavioral bias favors quick or assertive learners while neglecting those with reflective or slower-paced styles. Language model bias arises when LLMs misinterpret grammar or syntax from non-native speakers, leading to misleading or incorrect feedback.

Additionally, feedback loop bias can restrict learner growth by reinforcing narrow content paths and failing to introduce new or challenging material. On the other hand, educational content generation bias relates to how LLMs produce learning materials such as examples, case studies, and explanations. Cultural bias is evident when generated content centers predominantly around Western contexts, excluding global perspectives.

Stereotypical bias appears when the system reuses examples or narratives that reinforce societal stereotypes. Difficulty level bias results when over-personalization based on prior performance prevents students from accessing advanced material. Content bias reflects ideological or regional skew in the selection of facts, cases, or topics.

Finally, accessibility bias refers to the system's failure to design content with inclusive intent, potentially disadvantaging learners with disabilities or special needs. By identifying these types of bias, this taxonomy provides a foundation for systematic evaluation and targeted mitigation efforts in LLM-integrated educational systems.

#### IV. SURVEY OF LITERATURE

##### A. Bias in LLMs

Adaptive To synthesize and analyse the literature effectively, we organized the reviewed papers into thematic clusters. This clustering approach helps trace the evolution of research on bias in LLMs, from recognition to mitigation, and reveals interconnections between diverse contributions. The clustering was based on the core focus of each paper, including its primary research question, methodology, and contribution.

Four key clusters emerged:

- Recognition and Taxonomy of Bias
- Measuring and Diagnosing Bias
- Manifestations in Real-world Tasks
- Mitigation Techniques

Cluster 1: Recognition and Taxonomy of Bias

This cluster includes foundational work that highlights and categorizes the various forms of bias present in LLMs. These works establish the groundwork for why bias is a critical concern in educational and social contexts.

Cluster 2: Measuring and Diagnosing Bias

The second cluster includes papers focused on developing tools, benchmarks, and methodologies to evaluate bias in a structured way. These papers serve as a bridge between recognizing bias and formulating solutions.

Cluster 3: Manifestations in Real-world Tasks

Papers in this cluster demonstrate how bias manifests in applied settings such as educational feedback, information retrieval, and conversational agents. These studies underscore the real-world implications of unchecked biases.

Cluster 4: Mitigation Techniques This final cluster brings together research that proposes practical solutions for reducing bias. Techniques include knowledge graph augmentation, counterfactual data, prompt rephrasing, and reinforcement learning levels.

Summary of the understanding:

A growing body of literature has critically examined various biases in Large Language Models (LLMs) relevant to adaptive learning systems. Kim et al. [2] introduced a fairness framework for educational AI, advocating for ethical deployment in EdTech. Gender bias was prominently identified in teacher feedback generated by LLMs [5], [18], raising concerns about unequal treatment. Chen et al. [7] and Lehmann et al. [19] explored racial and political biases in AI-generated news, indicating risks of replicating skewed narratives in educational content.

Selection and retrieval biases affecting personalized content delivery were highlighted by Lee and Patel [15] and Bee et al. [15]. Tools for measuring and mitigating social biases across classification and generation tasks were developed by Tuli et al. [4], while Rajendran et al. [10] contributed benchmark suites to test LLMs for hallucinations and stereotyping. Yu et al. [6] demonstrated grading and rubric fairness issues in automated evaluation, with Costello et al. [8] analyzing intergroup bias using higher education datasets. To counter these issues, various mitigation strategies have been proposed—Huang et al. [3] employed knowledge graphs for fine-tuning, Chen et al. [11] used ensemble-based reasoning, and Zhan et al.

[10] introduced conformity bias detection. Further, real-time monitoring approaches were proposed by Sun et al. [12], and Liu et al. [13] designed scalable audit systems for institutional deployment. Collectively, these studies underscore the urgency of addressing LLM-induced bias in adaptive learning environments to promote fairness, accuracy, and inclusive.

### B. Adaptive learning integration with GenAI

The integration of Generative AI (GenAI), particularly large language models (LLMs), into adaptive learning systems marks a significant evolution in personalized education. Unlike traditional AI-based adaptive systems that rely on fixed algorithms and static datasets, GenAI-driven platforms enable real-time generation of content, dynamic learner feedback, and personalized learning pathways. However, this advancement also introduces new layers of complexity related to system transparency, pedagogical alignment, and bias mitigation. To synthesize the diverse developments in this space, we classify the literature into four thematic clusters:

- Architectural Enhancements and Functional Capabilities
- Pedagogical and Curriculum Design Innovations
- Learner Modelling and Engagement Optimization
- NLP-Driven Feedback and Assessment Systems. Cluster 1:

Architectural Enhancements highlights modular, GPT-based systems like AIIA and SocratiQ that enable personalized tutoring, real-time feedback, and content generation. These platforms integrate features such as Whisper ASR, semantic search, and adaptive pipelines. However, they risk introducing feedback and assessment biases due to data limitations and misinterpretation of student inputs.

Cluster 2:

Pedagogical and Curriculum Design explores the use of GenAI in automated syllabus and assignment creation. Models like GPT-3 and GANs support scalable curriculum development, as seen in projects like SHAPING AI. While effective in reducing instructor workload, concerns include content bias, linguistic dominance, and over-standardization that may neglect pedagogical depth.

Cluster 3:

Learner Modeling and Engagement Optimization involves tailoring content through learning style frameworks (e.g., VARK) and gamification. Systems like CogBooks dynamically adapt to learner behavior. Yet, reliance on limited behavioral data can lead to engagement and content biases, disadvantaging reflective or neurodiverse learners.

Cluster 4:

NLP-Driven Feedback Systems use sentiment analysis and behavior modeling to automate grading and feedback. These enhance personalization but risk sentiment misinterpretation, language bias, and rubric misalignment, potentially affecting learner motivation and fairness.

Summary of the understanding:

Recent AI innovations have significantly influenced adaptive learning (AL) systems, particularly through personalized and generative approaches. Integrating large language models (LLMs) has enabled real-time feedback and question generation, addressing pedagogical inaccuracies and content bias (Kumar et al., 2024 [22]). NLP-based platforms support summarization, quizzes, and lecture transcription, though they face risks like hallucinations and academic integrity concerns (Mehta et al., 2024 [23]).

Adaptive learning loops utilizing user profiling and modular LMS design combat the limitations of one-size-fits-all models (Sharma et al., 2025 [27]). Socratic dialogue frameworks further improve engagement and content delivery by addressing interaction and assessment bias (Rao et al., 2025 [28]).

Generative AI also facilitates curriculum development through automated syllabus generation and virtual labs, yet over-standardization and lack of hands-on learning remain challenges (Ramesh et al., 2024 [30]). Case-based and thematic analyses reveal ethical risks such as algorithmic bias and teacher disempowerment (Iyer et al., 2024 [25]). Predictive modeling tools used in grading and learning paths expose gaps in transparency and responsible AI use (Singh et al., 2024 [29]).

Learning style-based personalization—via VARK models or machine learning—helps improve engagement but faces issues of learner misrepresentation and implementation resistance (Meera et al., 2021 [19]; Thomas et al., 2023 [21]). Hybrid delivery models, such as CogBooks, manage cognitive overload and instructor variability (Patel et al., 2024 [24]).

Finally, NLP-enhanced feedback systems employing sentiment analysis and opinion mining offer nuanced personalization but raise concerns over cognitive and feedback interpretation biases (Verma et al., 2024 [18]; Nair et al., 2023 [20]).

### V. GAPS AND CHALLENGES IN BIAS DETECTION AND MITIGATION FOR ADAPTIVE LEARNING PLATFORMS

Despite the growing integration of Large Language Models (LLMs) into adaptive learning platforms, several critical gaps remain in ensuring fairness, transparency, and equity. While the literature has highlighted promising techniques for detecting and mitigating bias, these approaches are still underdeveloped or misaligned with the unique demands of educational environments.

#### A. Lack of Education-Specific Debiasing Tools

Most existing bias mitigation techniques are designed for general-purpose NLP or enterprise AI systems. They do not consider the pedagogical and cognitive dimensions critical to education, such as learner motivation, assessment fairness, or instructional tone. Tools like FairPy and Enterprise-Scale Bias Mitigation provide generic benchmarks and debiasing algorithms but are not tailored to the language and structure of academic feedback or educational content.

Example: Techniques effective in reducing gender bias in chatbots may not work for essay grading tools where nuanced language influences scoring decisions.

#### B. Underrepresentation of Global Learner Diversity

Many LLMs are trained primarily on Western-centric corpora, which reflects in both content generation and feedback quality. As seen in the OpenStax and ICNALE analysis, adaptive systems tend to favor native English expressions and Euro-American contexts. This results in educational content that lacks cultural, geographic, and linguistic diversity—undermining equitable global learning. Impact: Non-native speakers and students from underrepresented regions may receive less accurate, less engaging, or less relatable educational material and feedback.

#### C. Absence of Standard Evaluation Protocols

Currently, there is no universally accepted framework to evaluate bias in adaptive learning systems. Existing methods are fragmented, relying on ad hoc probes, case studies, or synthetic inputs. The lack of standardized test suites or benchmark tasks for educational fairness severely limits reproducibility and comparison across models. Need: A consistent evaluation pipeline—similar to GLUE or MMLU benchmarks for general LLMs—tailored to student assessments, feedback, and curriculum fairness.

#### D. Lack of Real-World Evaluation Frameworks

Most bias detection studies are conducted in controlled lab environments or through synthetic test prompts. There is a pressing gap in evaluating bias within actual classrooms or live adaptive systems. Without real-world deployment studies, we cannot measure how bias affects long-term learning outcomes, engagement, or self-perception.

Challenge: Translating theoretical detection methods (e.g., name probes or prompt rephrasing) into actionable insights for educators, developers, and policymakers.

Conclusion: Addressing these gaps is essential to move from theory to practice in bias mitigation. The next generation of adaptive learning systems must be designed with fairness, inclusivity, and real-world evaluation as core principles—not afterthoughts. This requires collaboration across educators, AI researchers, and policymakers to build trustworthy, equitable educational technologies.

TABLE I  
SUMMARY OF CHALLENGES AND PATH FORWARD

Challenge	Implication	Recommendation
No education-specific debiasing tools	Generic tools fail to handle academic tone/content	Develop LLM debiasing modules tailored for education
No standard evaluation protocols	Inconsistent and non-replicable studies	Create educational bias benchmarks and shared datasets
Global diversity underrepresented	Content fails to reflect linguistic and cultural plurality	Expand training data within inclusive educational sources
No real-world environment evaluation framework	Lack of practical validation in classrooms	Deploy pilot studies with feedback loops in real schools

## VI. FUTURE DIRECTIONS

To equitably integrate Large Language Models (LLMs) into adaptive learning platforms, research must shift from merely identifying bias to engineering systems that proactively prevent and correct it. Several strategic directions are proposed to guide this shift.

- 1) **Tailored Educational Benchmarks:** Existing benchmarks fail to capture context-specific biases. Future efforts should focus on developing task-specific datasets and evaluation protocols for real-world applications like essay grading and feedback tone analysis. Actionable Goal: Create benchmark suites assessing fairness across diverse demographics, writing styles, and educational levels.
- 2) **Multimodal and Multilingual Bias Mitigation:** Current models often ignore non-English content and multimodal inputs. Biases in speech-based tutoring, visual aids, and translations need urgent attention. Actionable Goal: Expand audits to include multilingual and multimodal contexts, especially for underrepresented learners.
- 3) **Student-Centered LLM Co-Design:** Most LLMs are developed without learner input. Involving students, particularly from marginalized groups, ensures relevance and fairness. Engage learners in the design and testing of prompts, interfaces, and evaluation metrics.
- 4) **Synthetic Student Profile Generators:** Controlled, privacy-safe testing can be enabled using synthetic profiles that vary in name, dialect, and writing style. Actionable Goal: Build open-source tools to simulate diverse learner characteristics for bias analysis.
- 5) **Education-Specific Bias Benchmarks:** This sector needs its own equivalent to GLUE or SuperGLUE, focused on fairness in content and assessment. Actionable Goal: Collaborate with educators to develop benchmark datasets.
- 6) **Equity-Driven LLM Tuning:** Fine-tuning must incorporate diversity and inclusion objectives beyond accuracy. Actionable Goal: Design tuning pipelines that encode fairness and representation.

In conclusion, proactive fairness engineering, co-design, and inclusive governance are essential for building ethical adaptive learning systems.

## VII. CONCLUSION

As generative AI continues to transform education, ensuring fairness in its integration is no longer optional—it is essential. Adaptive learning platforms powered by large language models (LLMs) hold immense promise for personalization, engagement, and scalability, but they also risk amplifying existing inequalities through biased feedback and culturally narrow content. This survey provides a foundational analysis of how bias manifests in GenAI-driven educational systems, particularly in automated feedback and content generation. By synthesizing recent research, proposing a taxonomy of biases, and highlighting gaps in detection and mitigation practices, this work establishes a roadmap for future, equity-centered AI in education. Ultimately, educational technologies must serve all learners regardless of background, language, or learning style. Achieving this requires not only innovation but also accountability, inclusivity, and the commitment to build systems that promote opportunity rather than reinforce disparities.

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