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

Lakshmi M Achar
St.Claret College Autonomous, India

***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 toeducation,italsoopensthedoortosomeseriouschallenges. Oneofthemainconcernsisbias.BecauseLLMslearnfrom datacollectedacrosstheinternet,theyoftenabsorbandreplicate stereotype sorculturalimbalances foundinthatcontent. These biasescanshowupinthefeedbackstudentsreceiveortheeducational materials generated, particularly disadvantaging those from non-dominant cultures, regions, or language backgrounds. Thispaperlookscloselyathowsuchbiasesappearintwo keyareasofadaptivelearning:feedbacksystemsandcontent creation. Byanalyzing 50recentresearchstudies,wehighlight wheretheproblemslie,howthey'vebeenstudied,andwhat solutions are emerging. We found that the way a student writesorthenametheyusecaninfluencetheresponsestheygetfroman AI.Somestudentsreceiveva gueoroverlycriticalfeedback,while othersmaynotseethemselvesreflectedinlearningexamplesatall.**

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.Butbybridgingthegapbetweentechnicaldevelopment andclassroomrealities,thispaperaimstoguidefutureefforts 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, andgeneratelearningcontentonthefly.Theirabilitytomimic human-likeresponsesandcontextualunderstandingalignswell withthegoalsofadaptivelearningplatforms(Kimetal.,2023 [2];Tulietal.,2023[4]).Whetheractingasvirtualtutors 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 trainedonmassivedatasetsfromacrosstheinternetdatathatoftenreflectssocietalbiases.Whenthesebiasesarecarriedintoeducationaltools,th econsequencescanbesubtlebut far-reaching. Studies show that feedback generated by LLMs may vary depending on how a student writes or the perceived backgroundofthelearner(Zhangetal.,2022[5];Costello etal.,2024[8]).Likewise,generatedcontentoftencenters Westernnormsandoverlooksdiverseculturalandregional perspectives (Chen et al., 2023 [7]; Lehmann et al., 2023 [7]). Thispaperexaminestwoareaswheresuchbiasismost likelytoappear:(1)automatedfeedbackandassessment, and(2)thegenerationof educationalcontent.Inthecaseof feedback,welookathowastudent'sphrasingorinferred identitycaninfluenceAIresponses (Linetal., 2023[5]; Zhang et al., 2024 [10]). For content generation, we consider how variables like race, gender, geography, and language are representedorleftoutinlearningmaterials(Beeletal.,2023[15];Lehmannetal.,2023[7]).Toexploretheseissues,wereview30recentstudiesat the intersection of bias detection in LLMs and their use in educationalsettings.Weevaluatedetectionmethods,mitigation strategieslikepromptengineeringandfine-tuning,andemerging tools for auditing model behavior (Tuli et al., 2023 [4]; Huangetal.,2023[3];Chenetal.,2023[11]).Wealso 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 theidentificationofmajorgapsincurrentpractices—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,ensuringthatfutureadaptivelearningplatformsare not only smart but also fair and inclusive for all learners.

II. BACKGROUND

A. EvolutionofAdaptiveLearningPlatforms

Adaptivelearningplatformshaveevolvedsignificantlyfrom 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 learningexperiences(AI-enabledAdaptiveLearningSystems, 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 con-tent,pacing,andassessments.Theseplatformsareincreasingly 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. CapabilitiesandRisksofLLMsinEducation

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 toolsineducationalsettings,enablingtaskslikeessaygrading, personalized tutoring, automated QA,and curriculum design (Generative AI and Its Impact on Personalized Intelligent TutoringSystems,2023[22];GenerativeArtificialIntelligence in Education, 2024 [29]).

Despitetheirutility,LLMsposeuniquechallenges.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. IntegrationofGenAIinEducationalEnvironments

The integration of GenAI into adaptive learning environments is still a developing field. Systems now incorporateNLP tools to personalize feedback, tailor learning paths, and automateassessment,butoftenwithoutstandardizedprotocols to ensure fairness and equity. This gap has prompted growing interestintoolsforbiasdetectionandmitigation(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:

- Feedbackgeneration
- ContentCreation
- TutoringandGrading
- AssessmentandGrading.

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 in-consistentacrossdifferentlearnerprofiles.Linguisticbias emerges when the system favors particular writing styles or penalizesnon-standardexpressions,oftendisadvantagingnon-nativeEnglishspeakers.Demographicbiasreferstodisparities in feed- back based on attributes like gender, ethnicity, or geographic origin.

Knowledgerepresentationbiasrewardsresponsesthatalign 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.

Stereotypicalbiasappearswhenthesystemreusesexamples 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 designcontentwithinclusiveinmind,potentiallydisadvantaging 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. BiasinLLMs

Adaptive To synthesize and analyses the literature effectively,weorganizedthereviewedpapersintothematicclusters. This clustering approach helps trace the evolution of research on bias in LLMs, from recognition to mitigation, and reveals interconnectionsbetweendiversecontributions.Theclustering was based on the core focus of each paper, including its primary research question, methodology, and contribution.

Fourkeyclustersemerged:

- RecognitionandTaxonomyofBias
- MeasuringandDiagnosingBias
- ManifestationsinReal-worldTasks
- MitigationTechniques

Cluster1:RecognitionandTaxonomyofBias

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.

Cluster2:MeasuringandDiagnosingBias

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

Cluster3:ManifestationsinReal-worldTasksPapers

in this cluster demonstrate how bias manifests in applied set- tings 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.

Summaryoftheunderstanding:

Agrowingbodyofliteraturehascriticallyexaminedvarious biasesinLargeLanguageModels(LLMs)relevanttoadaptive learning systems. Kim et al. [2] introduced a fairness frameworkfor educationalAI,advocatingfor ethicaldeployment 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, indicatingrisksofreplicatingskewednarrativesineducational content.

Selectionandretrievalbiasesaffectingpersonalizedcontent deliverywerehighlightedbyLeeandPatel[15]andBeeletal. [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]demonstratedgradingandrubricfairnessissuesinautomatedevaluation,withCostelloetal.[8]analyzingintergroup 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 etal.[11]usedensemble-basedreasoning,andZhangetal.

[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,thesestudiesunderscoretheurgency of addressingLLM-induced biasin adaptivelearning environments to promote fairness, accuracy, and inclusive.

B. AdaptivelearningintegrationwithGenAI

The integration of Generative AI (GenAI), particularlylargelanguagemodels(LLMs),intoadaptivelearningsystems marks a significant evolution in personalized education. Unlike traditional AI-based adaptive systems that rely on fixed algorithmsandstaticdatasets,GenAI-drivenplatformsenable 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:

- ArchitecturalEnhancementsandFunctionalCapabilities
- PedagogicalandCurriculumDesignInnovations
- LearnerModellingandEngagementOptimization
- NLP-Driven Feedback and Assessment Systems. Cluster 1:

ArchitecturalEnhancementshighlightsmodular,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,andadaptivepipelines.However,theyriskintroducing feedback and assessment biases due to data limitations and misinterpretation of student inputs.

Cluster2:

Pedagogical and Curriculum Design explores the use of GenAIinautomatedsyllabusandassignmentcreation.Models like GPT-3 and GANs support scalable curriculum development, as seen in projects like SHAPING AI. While effectivein reducing instructor workload, concerns include contentbias, linguistic dominance, and over-standardization that may neglect pedagogical depth.

Cluster3:

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

Cluster4:

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.

Summaryoftheunderstanding:

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]).

Adaptivelearningloopsutilizinguserprofilingandmodular 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 biasandteacherdisempowerment(Iyeretal.,2024[25]).Predictive modelingtoolsusedingradingandlearningpathsexposegaps in transparency and responsible AI use (Singh et al., 2024 [29]).

Learning style-based personalization—via VARK modelsor machine learning—helps improve engagement but faces issues of learner misrepresentation and implementation resistance (Meera et al., 2021 [19]; Thomas et al., 2023 [21]). Hybriddeliverymodels,suchasCogBooks,managecognitive 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 interpretationbiases(Vermaetal.,2024[18];Nairetal.,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. Whiletheliteraturehashighlightedpromisingtechniques for detecting and mitigating bias, these approaches are still underdeveloped or misaligned with the unique demands of educational environments.

A. LackofEducation-SpecificDebiasingTools

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,suchaslearnermotivation,assessmentfairness, 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 structureof 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. UnderrepresentationofGlobalLearnerDiversity

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 diver-sity—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. AbsenceofStandardEvaluationProtocols

Currently, there is no universally accepted framework to evaluate bias in adaptive learning systems. Existing methods arefragmented,relyingonadhocprobes,casestudies,orsyntheticinputs.Thelackofstandardizedtestsuitesorbenchmark tasks for educational fairness severely limits reproducibility and comparison across models. Need: A consistent evaluation pipeline—similartoGLUEorMMLUbenchmarksforgeneral LLMs—tailoredtostudentassessments,feedback,andcurriculum fairness .

D. LackofReal-WorldEvaluationFrameworks

Most bias detection studies are conducted in controlled lab environments or through synthetic test prompts. There is a pressinggapinevaluatingbiaswithinactualclassroomsorlive adaptive systems. Without real- world deployment studies, we cannotmeasurehowbiasaffectslong-termlearningoutcomes, engagement, or self- perception.

Challenge: Translating theoretical detection methods (e.g., nameprobesorpromptrephrasing)intoactionableinsightsfor educators, developers, and policymakers.

Conclusion: Addressing these gaps is essential to move fromtheorytopracticeinbiasmitigation.Thenextgeneration of adaptive learning systems must be designed with fairness, inclusivity, and real-world evaluation as core principles—not afterthoughts.Thisrequirescollaborationacrosseducators,AI researchers, and policymakers to build trustworthy, equitable educational technologies.

TABLEI
SUMMARYOFCHALLENGESANDPATHFORWARD

Challenge	Implication	Recommendation
No education-specificdebiasingtools	Generictoolsfail tohandleacademictone/content	DevelopLLMdebiasing modulestailoredforeducation
No standard eval-uationprotocols	Inconsistentandnon-replicablestudies	Createeducationalbias benchmarksandshareddatasets
Globaldiversity underrepresented	Contentfailstoreflect linguisticandculturalplurality	Expand training data withinclusiveeducationalsources
No real-environmentevaluationfra mework	Lackofpracticalval-idationinclassrooms	Deploypilotstudieswith feedbackloopsinrealschools

VI. FUTURE DIRECTIONS

ToequitablyintegrateLargeLanguageModels(LLMs)into adaptive learning platforms, research must shift from merely identifyingbiastoengineeringsystemsthatproactivelyprevent 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 toincludemultilingualandmultimodalcontexts,especiallyfor underrepresented learners.

3) Student-Centered LLM Co-Design: Most LLMs are developed without learner input. Involving students, particularly frommarginalizedgroups,ensuresrelevanceandfairness. Engagelearnersinthedesignandtesting of prompts, interfaces, and evaluation metrics.

4) SyntheticStudentProfileGenerators:Controlled,privacy-safetestingcanbeenabledusingsyntheticprofilesthatvaryin name,dialect,andwritingstyle.ActionableGoal:Buildopen-source tools to simulate diverse learner characteristics for bias analysis.

5) Education-SpecificBiasBenchmarks:Thesectorneedsits 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.

Inconclusion,proactivefairnessengineering,co-design,and inclusivegovernanceareessentialforbuildingethicaladaptive learning systems.

VII. CONCLUSION

AsgenerativeAIcontinuestotransformeducation,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, particularlyinautomatedfeedbackandcontentgeneration.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- centeredAI in education.

Ultimately, educational technologies must serve all learn-ers 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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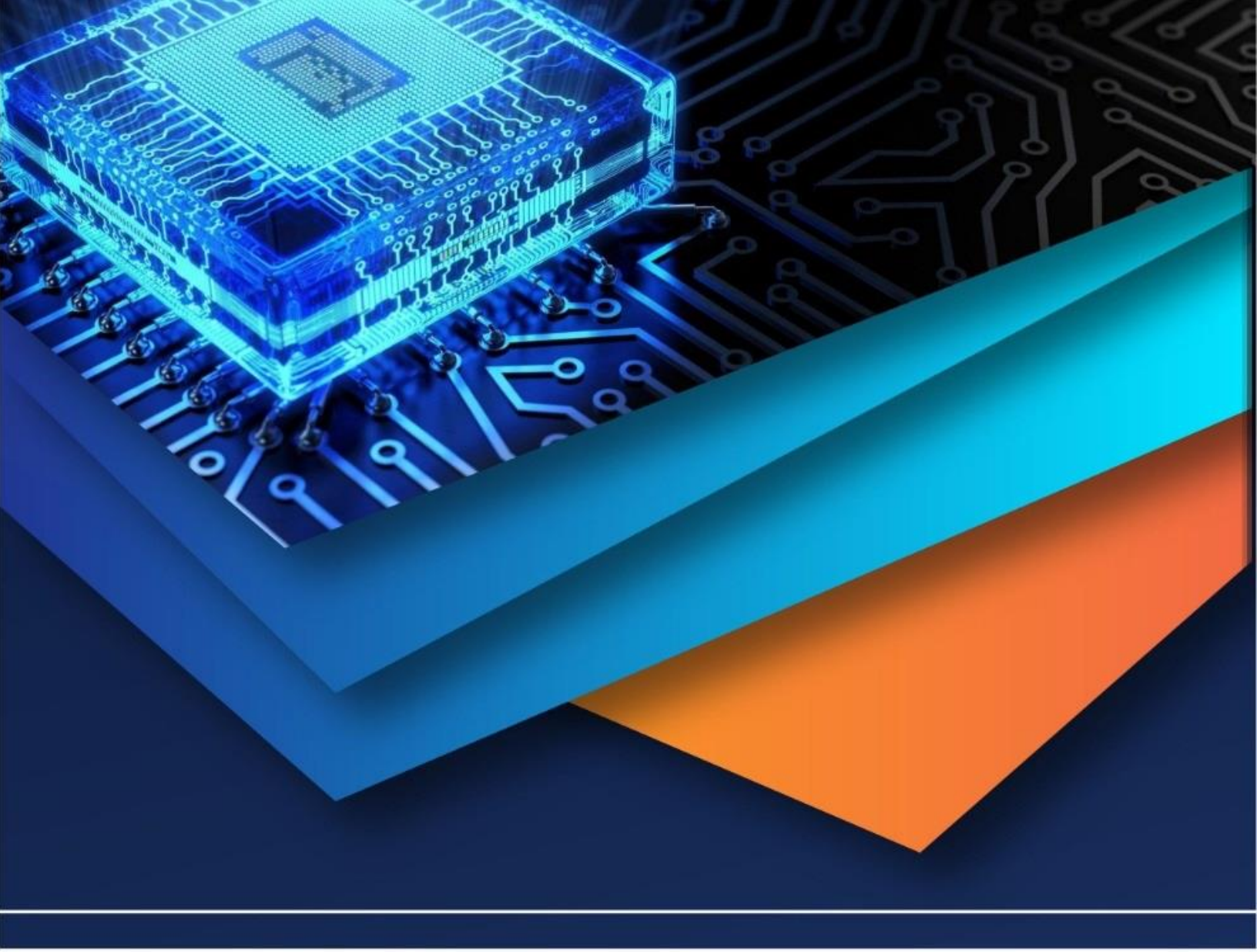

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