

Statistical Fairness Analysis of Generative Ai-based Educational Assessment Systems for Students with Disabilities

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ABSTRACT:

Generative Artificial Intelligence (GenAI) has started to play significant role in the field of Education (EDU), especially in Education Assessment & Feedback, Automated Grading & Education Personalisation. Its increasing popularity, however, has sparked a discussion about the need for fairness in determining students' abilities that is rooted in artificial intelligence for evaluating student performance. It's growing adoption, however, has raised the concerns of whether or not AI-based assessment would be equitable for disabled students. This article discusses, through a secondary review (literature-based review), the statistical fairness of educational assessment systems that make use of GenAI. It reflects important factors of fairness such as demographic parity, equal opportunity, equal odds and disparate impact, and explores the potential for differences in communication, behavior, response time and assistive technology related to disability to impact AI assessments. Based on the reported literature reviewed, overall accuracy of a strong, all-purpose AI does not always lead to equality of results for disability groups. Valid concerns range from the lack of disability-inclusive data and access issues, to model bias and issues with implementing traditional measures of fairness for different disability groups. The article suggests regular fairness audits, accessibility of the assessment design, inclusion of the necessary accommodation features, enhanced disability representation in assessment datasets and ongoing manual verification to facilitate equitable and reliable assessment using intelligence tools.

Keywords: Educational Assessment, Students with Disabilities, Statistical Fairness, Algorithmic Bias, Automated Assessment, Inclusive Education.

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1. Introduction

The educational landscape is changing rapidly, especially thanks to Generative Artificial Intelligence (GenAI), which is becoming a vital new part of the education system, and applications relying on large language models (LLMs) are increasingly being adopted for the purposes of assessment, grading, feedback and personalized learning. They will work quickly with large quantities of student's work and they can give uniform and prompt feedback. They can also assist with more flexible assessment guiding teachers to formulate questions, assess student answers and offer learning support (Hoernig et al., 2024). But the applications made of GenAI in assessment bring up not just questions about validity, reliability, transparency and fairness, but also significant concerns. Some recent studies have indicated that AI-based assessment has been found to be largely accurate, and yet there are differences between student groups; so accuracy cannot be considered a measure of "fairness" in assessment.

The fairness aspect is even more critical for the students with disabilities as their reading, writing, speaking, movement, and technology appropriation modes are not necessarily aligned to the pattern that is used in the generation of data for training and analyzing AI. However, there are potential adjustments to interaction with an AI system such as accessibility tools and reasonable assessment accommodations. This means that an AI system can sometimes react to a disability-related characteristic, and not the actual accomplishment of the student. Evidence examined in the field of AI applications in large-scale assessment has identified little evidence relevant to disability and the potential for accessibility issues and construct irrelevant variance in achievement scores for disabled students. So in this article, statistical fairness of the educational assessment system using GenAI from a second, literature-based analysis will be undertaken on the subject of students with disabilities. It deals with measures of fairness, sources of bias arising from disability, evidence from research, and assessment accommodations

and strategies to minimize unwanted consequences. The central concept is that an effective overall performance of good AI does not necessarily ensure equal opportunities for any subset of students so that fairness testing specific to disability is needed, as is human oversight.

2. GenAI-Based Educational Assessment and Disability Risks

Generative tools for educational assessment are becoming more prevalent and are now utilized for automated marking, scoring of written responses, the creation of questions, adaptive assessment, and feedback. These can aid teachers in their workload and give prompt responses to scholars (Arslan et al., 2024). Whether their benefits manifest or not though depends on whether they can rate a variety of students fairly and equitably. This is particularly true for students with disabilities, who may have unique ways of reading, writing, speaking, and moving, and of using technology, with the AI being set up to anticipate neurotypical patterns.

2.1. Automated Grading and Adaptive Testing: Accessibility Risks

Language patterns, content and other features of essays, short answers and other written works, can be graded automatically with an automated system. In addition, GenAI can generate questions and feedback and adaptively test the assessment content based on students' answers. These functions allow assessment to be achieved in a more expedient manner whilst allowing for a more personalized assessment. One question remains is whether the system takes meaning from what the student knows or what the learners says about that knowledge; and what is the effect of the latter on the former? For instance, if the signature is slightly different, the student may enter the subject you will be expecting but the AI score will be impacted because it took a little longer for the student to spell the word or use assistive technology to write the word in a particular format. Thus, accessibility should be taken into account when designing and evaluating their automated assessment systems.



Figure 1: Challenges and Opportunities of Generative AI for Higher Education

(Source: <https://www.mdpi.com>)

2.2. AI Proctoring and Behavior Monitoring: Risks of Disability-Related False Flags

Assessment misconduct could be detected by the use of facial monitoring, eye-gaze tracking, movement detection, voice analysis, behavior monitoring, and other monitoring systems available in AI proctoring systems. These are the instruments that should be used to ensure the integrity of assessments, but disability related behaviors might be viewed as unusual, or suspicious. Any sign of abnormal eye movements, involuntary movements, speech abnormalities or use of assistive devices can give out signals that are interpreted improperly by the AI system (Farhah et al., 2025). That's a chance for people to be mean and make incorrect shots. As a result, it is important to take the following steps when employing AI assessment systems: ensure that AI is not confounding disability-related behavior and academic dishonesty and to allow for human review prior to the making of any significant decisions.

3. Measuring Fairness in AI-Based Assessment

Statistical fairness allows to assess whether students of different groups will be assessed differently by an AI assessment system. Overall accuracy is important as it only reveals the overall performance of the system.

3.1. Main Statistical Fairness Measures for Disability Groups

Demographic Parity evaluates for equity if student groups realize positive outcomes at a similar rate. This could become an important tool in education evaluation when it comes to determining whether there are disparities between the percentage of a student with disability and the percentage of an able-bodied student receiving favorable assessment decisions. Equal outcome, however, does not necessarily imply fairness as different students may have a different level of prior success or level of needs and support (Khlaif et al., 2025). True-positive rates are the emphasis of Equal Opportunity. It enquires whether there is equity when it comes to the likelihood of getting a positive outcome on assessment between disability groups of students

who should achieve such a result. When the key issue is the ability of the AI to accurately identify qualified students, this is helpful. With Equalized Odds, both the true and false positive rates are compared. The question here is whether a potentially flawed AI system returns similar wrong and right results for different sets. It looks to see if the erroneous and accurate decisions that a possibly shoddy AI system makes are echoed across similar sets. This is appropriate when failing to take a chance could be as harmful as making a false positive one might be when it comes to student achievement (Kumar et al., 2026). Disparate Impact Ratio is a comparison of the ratio of positive outcomes in different groups. If there is a significant disparity it could be due to a lack of favorable outcomes in one group and may warrant further investigation.

3.2. Limits of Fairness Measures for Disability Groups

Implementing the measures to the disability population is not always easy. Pupils with a

disability are a diverse group with some kind of disability may be very few in a sample data set. The needs identified in the assessment may also vary from student to student according to the type of disability and/or the student may present with more than one disability. Simple group comparisons may not be useful to reflect these differences. Disability specific information may be further restricted from being collected and reported owing to privacy concerns. It is also crucial to distinguish the statistical significance from meaningfully and educationally disadvantaged experiences (Gupta, 2026). When there is a statistically significant difference, it implies that the difference could not simply have occurred by chance; it does not indicate, however, whether the difference is big or important in the education of students.

Table 1: Statistical Fairness Measures and Their Use in GenAI Educational Assessment

Fairness measure	What it measures	Use in disability assessment	Main limitation
Demographic Parity	Positive outcomes between groups	Checks similar favorable outcomes	Ignores actual achievement
Disparate Impact Ratio	Relative outcome rates	Identifies possible group disadvantage	May reflect achievement differences
Equal Opportunity	True-positive rates	Checks correct recognition of qualified students	Ignores false positives
Equalized Odds	True- and false-positive rates	Checks similar prediction errors	Needs reliable ground truth
Equal Opportunity Difference	Difference in true-positive rates	Identifies unequal correct recognition	Covers only true positives
False Positive Rate Difference	Difference in false positives	Identifies unequal incorrect decisions or flags	Ignores true-positive performance

4. Different Disability Groups and Different Forms of AI Bias

The effects of GenAI assessment extend beyond gender and incorporate differences in outcomes stemming from disability, which can have an impact on groups in different ways, introducing construct-irrelevant differences and accessibility issues.

4.1. Learning, Cognitive and Communication Disabilities

Students with dyslexia, dysgraphia and dyscalculia may have discrepancies in Reading, Spelling, Writing, Number Processing & Response Time. A machine-based grading system which relies heavily on spelling, grammar or writing style or speed may therefore not reflect the student's knowledge on the subject. Another example would be students whose speech or language skills are atypical may generate answers that vary from the language patterns taught to an AI system (Hong et al., 2026). Some differences have been observed when automated scoring is

compared to human scoring for test takers with speech and hearing impairments and higher speech-recognition error rates have been reported for some impaired groups.

4.2. Sensory and Physical Disabilities and Assistive Technology

Visual, hearing or physically disabled students may access screen readers, text to speech, speech to text, switch access, access to alternative keyboards and other assistive technology devices. These tools can eradicate obstacles and enable students to showcase their knowledge, but the AI system must accurately read in the resulting outputs. A speech pattern may be impacted by a disability, affecting speech recognition, for instance (Chauhan et al., 2026). Assistive technology may also alter the mode of access to an assessment, which also poses a question about whether the technology is eliminating a relevant or irrelevant barrier for a student, or unintentionally altering what the assessment is measuring.

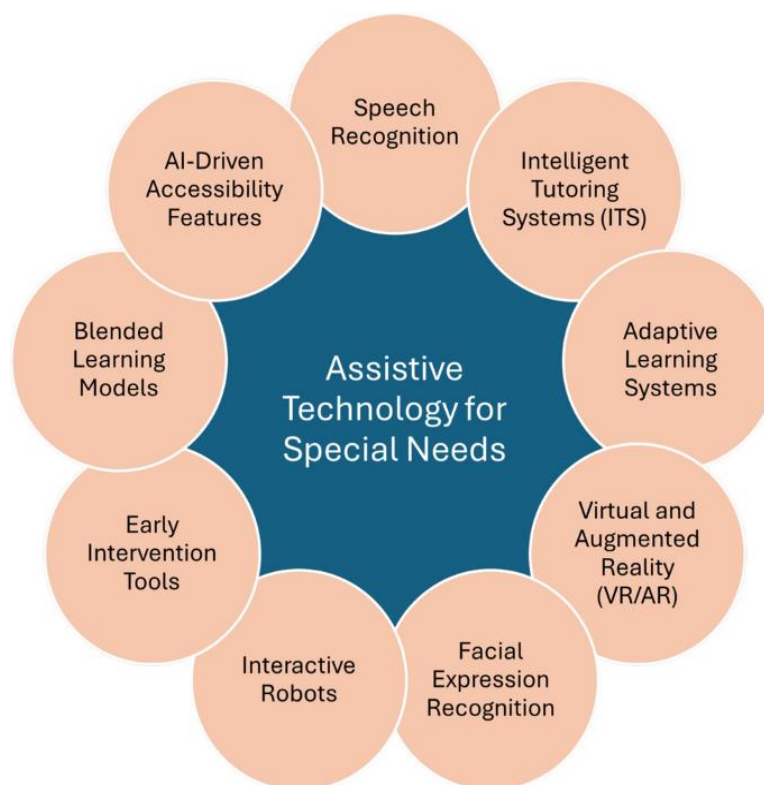


Figure 2: Assistive Technologies Supporting Students with Disabilities

(Source: <https://media.springernature.com>)

4.3. Neuro-divergence, Behavior and Different Interaction Patterns

Students with an Autistic profile or other 'neuro-divergent' profiles are likely to have different patterns of communication, response and interaction. Variations in eye contact, gestures, patterns of communication or lack of responsiveness could be interpreted as something different by a system built to match standard behavior. This is particularly important if there is a further level of behavioral monitoring or proctoring conducted as part of the assessment system. So it should not be based on a general disability classification of one kind or another (Clark et al., 2025). Do not assume that the same assessment system will be equally effective for all groups of disabilities. New AI testing, accessibility testing, and human evaluation efforts are essential to understanding that the differences in AI outcomes might be a result of disabilities or how the AI reacts to the disability attached to its associated attributes.

5. Main Sources of AI Bias Against Students with Disabilities

Bias in educational assessment can manifest in various aspects, from the data collection process to the creation and application of assessment models, and even through the interface or interactions with the system by students.

5.1. Limited Disability Representation and Assistive Technology Inputs

Training data for many AI systems may be limited that includes few examples of students with various disabilities. Underrepresentation may impair the ability of the system to identify diverse writing, speech and response patterns. A student who is using a screen reader, speech-to-text, keyboard or alternative keyboard to input data, may also be using input that is not the same as the data entered in training the system (Huggins-Manley and Booth, 2022). Unless these differences are taken into account, the AI may interpret an input to accessibility as lack of performance or unusual behavior. Hence, disability-inclusive training data and testing are

crucial to making assessments outcomes less unfair.

5.2. Response Time and Behavioral Bias

The response time, movement, gaze, speech timing and interaction style of users with disabilities may also be different to affect the ability of AI assessment systems and proctometers. A student may need to take longer to do something, or interact with the system in some different manner from the normal user. But if these indicators are assumed to indicate any issues with ability and suspicious activity, the results may not be fair (Sato et al., 2024). Problems like these reveal the importance of fairness in evaluating human systems of assessment: to distinguish between academic work and aspects of disability, and to ensure that there is human oversight of such automated judgments, when they could have significant consequences.

6. What Research Shows About Fairness in AI Assessment

Studies reveal that AI evaluation might have varied results on various student subgroups, and accuracy and fairness should be considered simultaneously, particularly for students with disabilities.

6.1. Fairness Issues in Automated Scoring

Studies of automated grade making demonstrate that the fairness might vary depending on the algorithm used, the training data set and the class. To investigate the effects of model differences, special education students were added to recent GenAI essay-scoring research, with no model being completely devoid of differences in subgroups. Strong overall performance was some of the models that also had varying results among groups. This is good proof that overall accuracy is not a sign of fairness (Schaller et al., 2024). Previous studies of automatic spoken-language scoring also reported discrepancies between the automatic and human scores of test takers with speech or hearing difficulties. Communication patterns may account for higher speech-recognition error rates in some disabled individuals, indicating that while automated

assessment can be used to identify the patterns, other disabled people may be identified as having higher rates of error. Thus, fairness issues can arise prior to issuing the final score, especially if the balls used for training do not exhibit varied communication.

6.2. Fairness Issues in AI Proctoring and Behavior Monitoring

There is less research in the area of disability specific AI proctoring. But there are some concerns regarding facial analysis, gaze tracking, movement detection and speech monitoring. Behaviours related to disabilities could mistakenly be seen as abnormal and suspicious activity. This can reduce the clarity of the results and lead to skewed outcomes. Therefore, it is important for human review prior to the impact of such flags on assessment decision making. However, fairness cannot be considered as a unique attribute of an AI assessment in the literature. The results are model- and data-dependent, dependent on the assessment tasks, dependent on the student groups and dependent on the fairness measures. Evidence supports the value of automated scoring over disability-specific proctoring, and demonstrates a need for increased disability-inclusive research (Yang et al., 2024). In most cases using AI will not ensure fairness of assessment, and to ensure that there is a fair assessment, AI systems must be vetted across relevant disability groups, and monitored for unequal outcomes.

7. Disability Accommodations and Fair Assessment

Fair AI assessment should support children and young people with disabilities in demonstrating their real knowledge which should not be hindered. Reasonable adjustments, including additional time, alternative format, screen reader, speech-to-text and accessible interfaces etc, can provide equal opportunities, not unfair advantages. These changes should be made to eliminate obstacles, but without altering assessment of the knowledge or skills. To make

this safe, it's essential that GenAI systems be tested for supported responses with various assistive technologies and that those responses are fairly understood and scored. Personalization of questions and feedback and response approaches are other possibilities for AI; however, the more personalized the approach, the more complicated it would be to compare student responses (Zhao et al., 2025). In the same manner, imposing uniformity of treatment in teaching the subjects and addressing the needs of each student may involve an injustice, especially where accessibility is different for students. The principles of a fair approach should support the provision of common learning standards with appropriate adjustments.

8. Reducing Bias and Auditing GenAI Assessment Systems

The process of combating artificial intelligence bias will be gradual, starting from the preparation of data, training, and finally within the decision-making phase. The pre-processing may impact the capacity to better represent the disabled person and may reduce the amount of imbalance in the training data since the pre-processing itself could be done using the training data. It might be determined at in-processing to the model that it will give fairness, or because it is being constructed the model may be reviewed at post-processing to determine if fairness is provided and adjust if necessary. One should be mindful of any possible trade-offs between using these techniques as it may affect another fairness measure, or the performance of the model itself. When the recommendation has an impact on students' academic honesty (grades, promotion, etc.), the accuracy of the recommendation is especially important (Rasooli et al., 2023). Teachers should make decisions about unusual or high impact decisions in consultation with assessment experts and disability experts. Accurately measures, error and level of fairness for disability groups regularly should be included in testing. Students should be able to appeal any misinterpretations or errors in decisions made.



Figure 3: Framework for Preventing, Detecting and Reducing AI Bias

(Source: <https://www.paloaltonetworks.com>)

9. Multimodal and Personalized AI: Fairer or More Biased?

Multimodal GenAI utilizes various student information such as written responses, speech, response time and interaction behavior to implement the system. Multiple sources might decrease reliance on a single potentially biased source, and offer a broader perspective on student performances. This may be beneficial for students with disabilities such as to provide a greater level of flexibility in assessment and provide alternative means for demonstrating knowledge. But there is no automatic assurance of fairness with the increased use of data. There can be a particular type of data which is inappropriate for a disability group and accessibility related behavior could be interpreted as ability or performance (Nieminen, 2023). Personalized systems are able to learn a pre-known pattern of bias from their training data as well. So, before deployment, an assessment should be multimodal to all disability groups and measures of fairness should be tested for any important source of data and for the overall

assessment result. There needs to be some human oversight on this process.

10. Real-World Challenges for Disability-Fair AI Assessment

Technical, financial, legal and organizational challenges arise in the two elements of implementing fair GenAI assessment in the real education context. The availability of disability inclusive datasets is one of the key challenges. In small and imbalanced datasets, it is hard to know if the small size of one group victimizes them, or is due to their rarity, and to determine if the AI system is functioning equitably across disability groups. Other considerations are privacy: potentially there may be sensitive information about disability that needs to be treated with caution and received with privacy. Institutions may also be lacking in the ability to evaluate and evaluate the combination of accessibility and the accuracy and statistical fairness of AI tools (Johnson, 2025). While there are accessibility and equality frameworks, such as the ADA and Section 508 in the US, these can offer good guidelines, but a system of assessment for an AI

cannot be deemed to be fair in practice without actually being fair in practice. The need for good governance means that there is a need for auditing and accountability. Students with disabilities, teachers, accessibility professionals and AI developers should be part of integrating a system design and AI system review in order to prevent practical barriers from impacting assessments.

11. Future Directions

Assessment systems should instead become ongoing, to avoid single-point failures in respect to fairness. Periodic fairly audits should provide a comparison, by disability group, of accuracy, percentage of errors and assessment results. There is also a greater need for more datasets that are inclusive of disability to enable AI models to learn from diverse communication, response and interaction styles. Universal Design for Assessments can be utilized to ensure assessment is accessible from the start, rather than in an ad hoc manner. It is also essential that the process of scrutineering be more transparent and how scores and decisions are being formed by AI must be explained clearly. For institutions to be able to

compare systems, standardizing fair reporting with common metrics may be helpful. Last, but not least, issues of accessibility and assessment specialists should also be included in the governance of AI.

12. Conclusion

It can be concluded that using generative AI to enhance learning assessment can be achieved through a number of ways including faster rating of work, feedback and personalized support but with accuracy comes fairness. Different risks may exist as a result of disability related communication, behavioral response, and/or accessibility needs by students with disabilities. The use of statistical measures of fairness can be useful to detect the unequal outcomes but a single measure does not encompass all aspects of fairness. Accommodations, accessible design, disability-inclusive data and human review and frequent fairness audits are all necessary for fair assessment. The larger aim is to be certain that AI assesses a student's factual knowledge and skills and not disability-related differences in their mode of communication or interaction with technology.

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