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Between Accessibility and Algorithmic Exclusion: Artificial Intelligence, Disability, and Inclusion in Higher Education – A Narrative Review of Evidence from 2020 to 2026

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Keywords: *artificial intelligence, higher education, inclusion, disability, deaf education, Libras, algorithmic bias, Universal Design for Learning*

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1. Introduction

Higher education systems worldwide continue to face persistent challenges in ensuring equitable access, permanence, participation, and academic success for students from diverse backgrounds. Students with disabilities, including deaf and hard-of-hearing students, students with learning disabilities, students with psychosocial disabilities, and students with physical or motor impairments, often encounter barriers that are not only pedagogical but also structural, attitudinal, linguistic, and technological (Davis, 2013; United Nations, 2006). These barriers become particularly visible when digital systems are introduced as neutral solutions without adequate attention to the conditions under which different students actually learn.

Against this backdrop, artificial intelligence has become a disruptive force in higher education. Since the public release of large language models such as ChatGPT in late 2022, universities have expanded the use of AI in tutoring, writing support, assessment, student monitoring, admissions processes, accessibility tools, and institutional services. Advocates argue that AI can make learning more flexible, personalized, and responsive to individual needs (Belay & Alamneh, 2026; Dumitru et al., 2026; Mallary, 2025). Critics warn, however, that AI may reproduce the same exclusions it claims to solve when it is built from biased data, designed for normative users, and implemented without student participation (Baker & Hawn, 2022; OECD, 2024; Pierrès et al., 2024).

In the Brazilian context, the relationship between AI and inclusion has a specific linguistic and legal dimension. Brazilian Sign Language (Libras) is legally recognized by Lei n. 10.436/2002 and regulated by Decreto n. 5.626/2005, which frame deaf people through visual experience and the use of Libras. For deaf students in higher education, inclusion cannot be reduced to captioning, automatic transcription, or generic accessibility. It requires recognition of Libras as a language, of deaf culture as a legitimate cultural-linguistic community, and of communication access as a rights-based condition for participation (Brasil, 2002, 2005, 2015).

This article reviews evidence from 2020 to 2026 to examine whether AI is currently functioning as an inclusive infrastructure in higher education or whether it remains a promise unevenly distributed across groups. The review is organized around three axes: (1) AI-powered assistive technologies for students with disabilities; (2) AI-driven personalization and Universal Design for Learning; and (3) algorithmic bias and ethical governance. The final sections identify research gaps, implications for policy and practice, and limitations of the current evidence base, with particular attention to Brazil and to the emerging field of Libras-AI research.

2. Scope and approach

This article adopts a narrative review approach. The objective is not to claim exhaustive coverage of all publications on AI and inclusion, but to synthesize the most relevant evidence, conceptual frameworks, and policy discussions for higher education between 2020 and 2026. Narrative reviews are appropriate when a field is rapidly evolving, methodologically heterogeneous, and still consolidating its categories of analysis. Because AI in inclusive higher education includes empirical studies, systematic reviews, conceptual articles, policy reports, and grey literature, a narrative synthesis allows the discussion to integrate evidence across different types of sources while maintaining a critical stance.

Targeted searches were conducted in PubMed/MEDLINE, Scopus, Web of Science, ERIC, CAPES Journals Portal, Google Scholar, and selected institutional repositories. Search terms combined variations of artificial intelligence, generative AI, machine learning, higher education, inclusion, disability, accessibility, deaf students, Libras, sign language, Universal Design for Learning, algorithmic bias, equity, and educational governance. Sources were included when they addressed AI in education or higher education and contained direct relevance to inclusion, disability, accessibility, deaf education, UDL, or algorithmic equity. Sources were excluded when they focused exclusively on K-12 education without transferable implications for higher education, described AI in education without an inclusion component, or provided purely technical model descriptions without educational or accessibility implications.

The final corpus presented in Table 1 includes 20 sources selected for thematic relevance and evidentiary contribution. The corpus includes peer-reviewed reviews, empirical studies, conceptual articles, legal and policy documents, and practice-oriented reports. Two Brazil-based studies conducted by members of the authorship team were included because they address the specific gap of Libras-AI and deaf inclusion in Brazilian higher education. To reduce the risk of self-citation bias, those studies are treated as context-specific contributions and interpreted alongside international evidence rather than as sufficient evidence on their own.

This review does not include meta-analysis, formal quality scoring, or PRISMA-style screening. Therefore, its findings should be read as a critical synthesis and agenda-setting contribution rather than as a systematic estimate of intervention effectiveness. This limitation is addressed explicitly in the final sections.

Table 1. Evidence base included in the narrative review ($n = 20$)

No.	Source	Type and context	Contribution to the review
1	Dumitru et al. (2026)	Integrative review; higher education; students with disabilities	Maps AI applications for accessibility, personalized learning, adoption challenges, institutional barriers, and implementation practices.
2	Belay & Alamneh (2026)	Systematic review; learners with disabilities	Synthesizes evidence on AI and machine learning support for learners with disabilities and highlights uneven methodological quality.
3	Pierrès et al. (2024)	Scoping review; higher education and disability	Warns that AI may treat disability as statistical outlier status when systems are not co-designed with disabled users.
4	Pagliara et al. (2024)	Scoping review; inclusive education	Organizes AI use in inclusive education and discusses ethics, privacy, personalization, and disability inclusion.
5	Cotilla Conceição & van der Stappen (2025)	Rapid review; inclusivity in higher education	Shows that AI benefits are unevenly distributed and that institutional efficiency often receives more attention than inclusion.
6	Mallary (2025)	Conceptual/review; adult and continuing higher education	Links generative AI to UDL through adaptive feedback, multilingual support, rubrics, and faculty development.
7	Ayala (2024)	Conceptual article; UDL and disability support	Frames ChatGPT as a possible UDL tool for stigma-free, on-demand academic support while noting ethical concerns.
8	Hyatt & Owenz (2024)	Empirical/conceptual teaching study; UDL-AI	Discusses UDL and AI assignments that can increase flexibility for students with disabilities when guided by accessible design.
9	Paglialunga & Melogno (2025)	Systematic review; learning disabilities	Finds promising effects of AI-based interventions for learning disabilities but emphasizes risk of bias and lack of longitudinal evidence.
10	Zhao, Cox, & Chen (2025)	Empirical study; students with disabilities in higher education	Documents how disabled students use generative AI for academic writing and identifies concerns about accuracy, integrity, cost, and training.
11	OECD (2024)	Policy report; equity and inclusion in education	Identifies allocative and representational harms and situates algorithmic bias as a systemic equity risk.
12	Gibson/EDUCAUSE (2024)	Practice report; accessibility and disability	Reports accessibility potential of AI and emphasizes that disabled users remain underrepresented in product development.
13	Baker & Hawn (2022)	Peer-reviewed review; algorithmic bias in education	Provides a foundational synthesis of how educational algorithms can reproduce racial, socioeconomic, and disability-related inequities.
14	Boateng & Boateng (2025)	Conceptual review; educational decision-making	Discusses self-reinforcing cycles of inequality in AI-driven educational systems.
15	European Parliament & Council (2024)	Regulation; European Union AI Act	Classifies certain AI systems in education and vocational training as high risk, requiring stronger governance and oversight.
16	UNESCO (2021)	International policy framework	Establishes human-rights-based ethical principles for AI, including transparency, redress, and inclusion.
17	Teach Access & Every Learner Everywhere (2025)	Higher education accessibility guide	Offers practical guidance on evaluating AI tools through accessibility and disability inclusion lenses.
18	Tishcoff et al. (2024)	Policy/practice report; higher education accessibility	Examines how generative AI may make learning more accessible while also creating new risks around equity and policy.
19	Santos, Schubert, Lima et al. (2025)	Brazilian literature review; Libras-AI	Maps scientific production on Libras and AI from 2019 to 2025 and identifies gaps in sign-language AI tools in Brazil.
20	Dos Santos, Morais et al. (2026)	Brazilian qualitative study; deaf inclusion	Foregrounds deaf community perspectives on AI, accessibility, and barriers in Brazilian higher education.

Rows 19 and 20 highlight Brazil-based studies directly connected to the Libras and deaf inclusion context discussed in this review.

3. AI-Powered Assistive Technologies for Students with Disabilities

3.1. Overview of the technology Landscape

AI-powered assistive technologies include automatic speech recognition, real-time captioning systems, text-to-speech and speech-to-text applications, AI-enhanced screen readers, predictive text, word completion tools, intelligent tutoring systems, adaptive feedback platforms, and conversational agents. These technologies address barriers that have historically limited access to higher education for students with sensory, cognitive, motor, and learning disabilities (Belay & Alamneh, 2026; Dumitru et al., 2026).

The evidence suggests real potential but also uneven maturity. Dumitru et al. (2026) identify AI and personalized learning, assistive technology benefits, implementation challenges, and best practices as central themes in the literature. Belay and Alamneh (2026) similarly report positive effects of AI and machine learning for learners with disabilities, while noting that only a portion of available studies meet rigorous methodological criteria. Paglialunga and Melogno (2025) offer a particularly important caution: AI-based interventions for learning disabilities show promising outcomes, but the current evidence base contains methodological weaknesses, limited long-term follow-up, and risk of publication bias.

3.2. Deaf Students, Libras, and AI in Brazil

Deaf and hard-of-hearing students occupy a specific position in AI-mediated inclusion because access is not only a matter of hearing support but also of language, culture, and visual communication. Automatic captioning may support some students, but it does not replace access in sign language. Sign language recognition and sign-language translation technologies remain underdeveloped for many national sign languages, especially when compared with dominant spoken languages. In Brazil, this challenge is intensified by the low-resource status of Libras in AI datasets and by the regional, cultural, and grammatical complexity of the language.

The literature review by Santos, Schubert, Lima et al. (2025) maps scientific production on Libras and AI from 2019 to 2025 and identifies a field that is growing but still technically and socially limited. The main gaps include small and non-representative datasets, insufficient attention to regional variation, limited involvement of deaf users in design and testing, and weak connection between prototype development and actual higher education practice. The qualitative study by Dos Santos, Morais et al. (2026) complements this picture by foregrounding the lived experience of deaf people in Brazil. Participants reported barriers related to AI captioning, institutional systems that are not prepared for Libras, and the absence of systematic consultation with deaf communities before new technologies are adopted.

These findings reinforce a central argument of this review: AI cannot be considered inclusive merely because it automates communication. In deaf education, inclusive AI must recognize the linguistic rights of sign-language users, involve deaf communities and interpreters in design, and be evaluated in real learning situations rather than only through technical accuracy metrics.

3.3. Participation Gaps in AI design

A recurring problem across the reviewed literature is the underrepresentation of students with disabilities in the design, procurement, implementation, and evaluation of AI educational tools. Gibson (2024) highlights the mismatch between the promise of AI accessibility and the limited representation of disabled users in product development. Pierrès et al. (2024) make this concern more explicit by warning that AI systems may classify disability-related patterns as anomalies, outliers, or noise when disabled users are absent from training data and design processes.

This participation gap has practical consequences. Tools built for an assumed normative learner may fail to recognize disabled students as legitimate users. They may also transfer the responsibility for accessibility from institutions to individuals, requiring students to adapt themselves to the tool rather than requiring the tool and the institution to remove barriers. In higher education, this is especially problematic because access is not an optional enhancement; it is a condition for equal academic participation.

4. AI-Driven Personalization and Universal design for learning

4.1. Personalization at Scale

One of the most frequently cited promises of AI in higher education is personalization. Adaptive platforms and generative systems can adjust explanations, pacing, content formats, examples, reading levels, feedback, and practice opportunities according to learner needs (Mallary, 2025). For students with disabilities, this flexibility can reduce dependence on fixed formats and allow more individualized access to academic content. For deaf students, AI-mediated personalization could support visual materials, bilingual resources, simplified summaries, and asynchronous review of content when it is embedded in a broader accessibility strategy.

However, personalization should not be confused with privatized responsibility. A system that allows each student to fix access barriers alone does not necessarily make the institution inclusive. The strongest potential of AI emerges when personalization is connected to Universal Design for Learning, not when it becomes a substitute for institutional accessibility, human support, or legally guaranteed accommodations.

4.2. Udl as a framework for Inclusive AI

Universal Design for Learning is a key framework for interpreting AI inclusion because it shifts the focus from retrofitting accommodations to designing flexible learning environments from the beginning. UDL emphasizes multiple means of representation, action and expression, and engagement. AI can support this framework by generating alternative explanations, multimodal materials, adaptive practice, multilingual support, rubrics, formative feedback, and individualized study strategies (Ayala, 2024; Hyatt & Owenz, 2024; Mallary, 2025).

Generative AI has made this relationship more visible. Students can ask for explanations in different formats, generate outlines, simplify complex texts, translate concepts, draft study questions, and receive immediate feedback. Zhao, Cox, and Chen (2025) show that students with disabilities are already using generative AI for academic writing and support tasks, especially through chatbots and rewriting tools. At the same time, they report concerns about accuracy, academic integrity, subscription costs, and the need for institutional AI literacy support. These findings suggest that UDL-oriented AI requires guidance, transparency, and training rather than unrestricted or unsupported adoption.

4.3. Implementation Gaps

The evidence shows a gap between conceptual promise and institutional practice. Cotilla Conceição and van der Stappen (2025) argue that AI tools in higher education often prioritize efficiency, automation, and institutional management more than inclusion. Students with more digital literacy, stronger prior academic capital, and access to paid tools are more likely to benefit from AI, while first-generation students, low-income students, disabled students, and linguistic minorities may face new forms of exclusion.

In Brazil, these concerns are amplified by infrastructure inequalities, variable access to assistive technologies, scarcity of Libras-capable AI tools, and institutional dependence on human interpreters whose availability is often limited. Therefore, AI integration must be accompanied by accessible procurement criteria, teacher and staff training, student-facing AI literacy programs, and mechanisms for monitoring whether benefits are equitably distributed.

5. Algorithmic Bias and Ethical Risks

5.1. How Bias Becomes Educational Infrastructure

Algorithmic bias occurs when AI systems trained on historical or non-representative data produce outputs that systematically disadvantage particular groups. In education, this can affect admissions, automated assessment, learning analytics, risk prediction, feedback, tutoring recommendations, accessibility tools, and student support allocation (Baker & Hawn, 2022; OECD, 2024). The problem is not simply that a model may be inaccurate. The deeper concern is that the inaccuracy may follow existing patterns of inequality and then be scaled across institutions.

For deaf students in Brazil, bias may appear when speech recognition systems are trained primarily on hearing speakers of standard Portuguese and fail to process deaf-accented Portuguese, sign-language users, or bilingual deaf communication practices. For students with learning disabilities, bias may appear when writing support or automated assessment tools interpret nonstandard language patterns as deficiency rather than as variation. For racialized, low-income, first-generation, or linguistically minoritized students, bias may appear in predictive systems that use historical performance, attendance, or platform behavior as proxies for future academic potential.

5.2. High-Stakes Decisions and data Sovereignty

AI is increasingly used in decisions that have material consequences for students: admission, scholarship eligibility, academic warning, retention interventions, plagiarism detection, accessibility triage, and resource allocation. When such systems are opaque, students may not know how they are being evaluated, which data are used, or how to contest an algorithmic decision. This creates serious concerns about informed consent, data sovereignty, and institutional accountability (OECD, 2024; UNESCO, 2021).

The risks are intensified when AI tools are imported from contexts with different linguistic, legal, and cultural assumptions. A tool developed in English-speaking higher education may not perform adequately in Portuguese, Libras, Indigenous languages, or multilingual academic environments. Similarly, tools that assume continuous digital engagement may misclassify students who share devices, work during the day, have unstable internet access, or rely on accessibility routines that are invisible to the data system.

5.3. Ethical and Regulatory Responses

Regulatory and ethical frameworks increasingly recognize the risks of AI in education. The EU Artificial Intelligence Act classifies certain AI systems used in education and vocational training as high-risk when they determine access, admission, assignment, learning outcomes, educational level, or monitoring during assessments (European Parliament & Council, 2024). UNESCO (2021) provides a human-rights-based framework emphasizing transparency, accountability, non-discrimination, and redress.

In Brazil, the Lei Brasileira de Inclusão (Lei n. 13.146/2015), the Lei Geral de Proteção de Dados Pessoais (Lei n. 13.709/2018), and the ongoing debate around the Marco Legal da Inteligência Artificial provide important but incomplete foundations. The Brazilian AI bill should be cited as Projeto de Lei n. 2.338/2023 rather than as an enacted law. At the time of revision, there is still no specific national instrument requiring bias audits, accessibility validation, or deaf-community consultation for AI tools used in higher education. This gap creates a policy opportunity: Brazil can align AI governance with disability rights, data protection, and linguistic justice before exclusionary systems become institutional defaults.

6. Gaps in the Literature and research Priorities

This review identifies five research gaps that should guide future studies and institutional action. The first is the absence of co-designed Libras-AI tools. Current research on sign-language AI in Brazil remains limited by small datasets, insufficient regional representation, and weak participation of deaf users and interpreters in design and evaluation (Santos, Schubert, Lima et al., 2025).

The second gap is the lack of longitudinal evidence. Many studies describe promising short-term outcomes, but few examine whether AI assistive tools improve retention, graduation, autonomy, academic confidence, or long-term learning outcomes for students with disabilities (Belay & Alamneh, 2026; Paglialunga & Melogno, 2025).

The third gap is the underrepresentation of specific disability groups. Students with psychosocial disabilities, chronic illness, multiple disabilities, deafblindness, and complex communication needs remain underrepresented in AI education research. The field also needs more intersectional evidence that analyzes disability together with race, income, gender, language, territory, and digital access.

The fourth gap is the scarcity of Global South and Brazilian higher education evidence. Much of the international literature is concentrated in North America and Western Europe. Brazilian federal institutes, community universities, regional institutions, Indigenous and quilombola students, and deaf communities remain underrepresented in the evidence base.

The fifth gap is the absence of a validated AI inclusivity assessment framework for Brazilian higher education. Institutions need criteria to evaluate whether an AI tool is accessible, linguistically appropriate, transparent, auditable, privacy-respecting, and aligned with disability rights before it is adopted.

7. Discussion

The evidence synthesized in this review presents AI in higher education as both an opportunity for reducing barriers and a mechanism through which old exclusions may be reorganized in new technological forms. The studies included in the corpus do not support a simplistic conclusion that AI is either emancipatory or harmful. Rather, they suggest that the inclusive value of AI depends on the social, institutional, linguistic, and ethical arrangements that surround its use. In this sense, AI should not be evaluated only by technical performance, speed, or novelty, but by its capacity to expand participation, protect rights, and redistribute access to learning conditions that have historically been unevenly available to students with disabilities and other marginalized groups.

A first point that emerges from the reviewed literature is that AI-based accessibility must be understood as infrastructure rather than as an isolated assistive add-on. Dumitru et al. (2026) and Belay and Alamneh (2026) show that AI can support students with disabilities through speech recognition, text-to-speech, writing assistance, adaptive learning systems, intelligent tutoring, and automated feedback. However, both reviews also indicate that positive results are closely associated with implementation quality. A tool may be technically available, but still fail as an inclusion strategy if students do not receive training, if teachers do not know how to integrate it into course design, if the platform is not compatible with assistive technologies, or if the institution lacks policies for privacy, procurement, and accountability.

This finding is important because much of the enthusiasm around AI in higher education still treats accessibility as a matter of individual compensation. From this perspective, a student who cannot access a standard learning environment is expected to use a tool to overcome the barrier alone. The reviewed studies suggest the opposite: AI becomes inclusive when it changes the environment, not only when it helps an individual survive an inaccessible environment. This distinction aligns with the social model of disability and with Universal Design for Learning. The barrier is not located only in the student's body, language, or cognition; it is also located in rigid curricula, inaccessible platforms, untrained staff, and assessment practices that privilege a narrow profile of academic performance.

A second point concerns the uneven maturity of evidence across disability groups. The strongest claims in the literature are still concentrated around learning disabilities, academic writing, adaptive feedback, and general assistive technologies. Paglialunga and Melogno (2025), for example, identify promising results for AI-based interventions for students with learning disabilities, but also emphasize methodological limitations, risk of bias, and scarcity of longitudinal evidence. Zhao, Cox, and Chen (2025) add an important empirical dimension by showing that students with disabilities already use generative AI to support academic writing, organization, comprehension, and revision. Yet these students also report concerns related to accuracy, cost, academic integrity, and the absence of institutional guidance. The implication is clear: students are adopting AI faster than universities are building inclusive governance around it.

This mismatch between student use and institutional policy is one of the most urgent issues for higher education. When AI tools are adopted informally, benefits tend to be distributed according to prior advantage. Students with stable internet, paid subscriptions, stronger digital literacy, and informal networks of support are more likely to benefit. Students who most need accessibility may face subscription barriers, lack of training, fear of being accused of academic misconduct, or uncertainty about whether the use of AI is permitted. Therefore, AI inclusion cannot depend on silent individual experimentation. Institutions need clear, accessible, and disability-aware guidance that explains which tools may be used, how they may be used, what their limits are, and how students can request support without stigma.

A third point, especially relevant to Brazil, is that automatic communication access cannot be confused with linguistic justice. In the case of deaf students, captioning and transcription may be useful, but they do not replace Libras. The Brazilian legal framework recognizes Libras as a language, not as a secondary accommodation or a visual version of Portuguese. For this reason, AI tools designed only around spoken or written Portuguese may reproduce exclusion even when they appear accessible. A deaf student may receive an automatic transcript and still remain excluded from the linguistic, cultural, and interactional conditions required for full academic participation.

The Brazil-based studies included in this review reinforce this point. Santos, Schubert, Lima et al. (2025) identify a growing but still fragile field of research on Libras and AI, marked by small datasets, limited regional representation, and insufficient involvement of deaf users in design and validation. Dos Santos, Morais et al. (2026) complement this technical diagnosis with community-based evidence, showing that deaf participants perceive AI as potentially useful, but remain concerned about tools that ignore Libras, reduce accessibility to captions, or are implemented without consultation. Together, these studies show that the central problem is not simply the absence of technology, but the absence of participatory, linguistically grounded, and culturally accountable technology.

This discussion also exposes the limits of treating sign-language AI as a universal technological problem. Sign languages are natural languages with their own grammar, spatial organization, regional variation, cultural markers, and embodied forms of meaning. A model trained on one sign language cannot simply be transferred to Libras without linguistic loss. Even within Libras, regional variation and community practices matter. Therefore, the development of AI for deaf inclusion in Brazil requires datasets that are ethically built, regionally diverse, and validated with deaf communities. It also requires the participation of Libras interpreters, deaf educators, linguists, accessibility professionals, and students who use the tools in real academic contexts.

A fourth point concerns the relationship between AI and UDL. Ayala (2024), Hyatt and Owenz (2024), and Mallary (2025) suggest that generative AI can operationalize several UDL principles by offering multiple forms of representation, expression, feedback, and engagement. A student may ask for a complex text to be summarized, translated into simpler language, reorganized as a study guide, converted into questions, or explained through examples. These affordances are particularly relevant for students with disabilities because they reduce dependence on a single format of teaching. However, the UDL value of AI depends on whether the institution uses AI to redesign learning environments or merely to provide optional tools at the margins.

The most inclusive scenario is not one in which AI replaces teachers, interpreters, accessibility professionals, or peer interaction. It is one in which AI expands the range of pedagogical options available to human actors. For example, AI may help faculty generate alternative formats, prepare accessible rubrics, anticipate barriers in course materials, or provide formative feedback before final assessment. It may help students rehearse academic writing, review content asynchronously, organize study routines, and clarify doubts without fear of embarrassment. But these uses require human mediation, because AI systems can hallucinate information, reproduce bias, simplify complex concepts inadequately, or generate outputs that are not aligned with course objectives. Inclusive AI is therefore not autonomous AI; it is supervised, contextualized, and pedagogically integrated AI.

A fifth point is that algorithmic bias should be interpreted as a rights issue rather than merely as a technical defect. Baker and Hawn (2022) demonstrate that educational algorithms can reproduce inequities related to race, socioeconomic status, disability, and prior educational opportunity. The OECD (2024) similarly distinguishes allocative harms, which affect access to resources or opportunities, from representational harms, which affect how groups are described, valued, or made visible by systems. In higher education, both types of harm are relevant. A predictive system may allocate less support to students whose learning patterns do not match historical data. A writing tool may frame multilingual or disability-related language variation as deficiency. A speech-recognition tool may fail to process deaf-accented Portuguese or other non-normative speech patterns. In each case, the harm is not only inaccurate output; it is institutional misrecognition.

Boateng and Boateng (2025) extend this concern by warning that AI-driven educational decisions may create self-reinforcing cycles of inequality. If a system predicts that certain students are at risk based on historical patterns shaped by exclusion, then institutions may unintentionally normalize lower expectations or more restrictive interventions for those students. This is especially dangerous in contexts where disability, poverty, race, language, and digital access intersect. For this reason, inclusive AI governance must include auditability, human oversight, mechanisms of contestation, and transparency regarding which data are used and for what purposes. Students must not be governed by systems they cannot understand or challenge.

The regulatory literature points in the same direction. UNESCO (2021) frames AI ethics through human rights, transparency, accountability, and non-discrimination. The European Parliament and Council (2024) classify several AI systems used in education and vocational training as high risk, especially when they influence access, admission, evaluation, monitoring, or educational progression. These frameworks are relevant for Brazilian higher education because they show that AI governance is no longer optional. Even when local regulation remains incomplete, universities and federal institutes can adopt internal standards that anticipate stronger governance requirements. Such standards should include accessibility testing, data protection analysis, algorithmic impact assessment, and consultation with affected communities.

A sixth point concerns institutional responsibility. Cotilla Conceição and van der Stappen (2025) argue that higher education institutions often emphasize efficiency and automation more than inclusion. This is a critical warning. AI can make administrative systems faster while leaving students less heard. It can accelerate decision-making while reducing transparency. It can create an appearance of personalization while deepening dependence on commercial platforms. For public institutions, particularly in the Global South, the question is not only whether AI works, but whose interests it serves, who pays for it, who controls the data, and who is excluded when it fails.

Practice-oriented reports also emphasize this institutional dimension. Teach Access and Every Learner Everywhere (2025) and Tishcoff et al. (2024) recommend that institutions evaluate AI tools through accessibility, usability, transparency, and equity criteria before adoption. Gibson (2024) similarly notes that disabled users remain underrepresented in product development, despite being central to claims about AI accessibility. These contributions suggest a practical agenda: accessibility should be built into procurement, contracts, pilot studies, faculty development, help-desk support, and student feedback systems. Institutions should not wait for students to complain after harm occurs; they should test for exclusion before scaling the tool.

For Brazilian higher education, the discussion leads to a specific policy and practice model. Inclusive AI should be guided by five principles: rights, participation, linguistic justice, evidence, and accountability. Rights means that AI must comply with disability law, data protection, and the educational right to reasonable accommodation and equal participation. Participation means that disabled students, deaf students, interpreters, and accessibility professionals must be involved before, during, and after implementation. Linguistic justice means that Libras and other minoritized languages must be treated as central design requirements, not as afterthoughts. Evidence means that tools should be evaluated through learning outcomes, retention, student experience, accessibility performance, and bias monitoring. Accountability means that institutions must define responsibility when an AI system produces harm, error, exclusion, or discrimination.

These principles also help clarify what should not happen. AI should not be used to replace Libras interpreters when communication access requires human linguistic mediation. It should not be used to deny accommodations because a tool is presumed to be sufficient. It should not be used to monitor students without transparency or consent. It should not be adopted only because it promises efficiency, novelty, or reduced costs. Above all, AI should not shift responsibility for inclusion from the institution to the student. The strongest evidence in this review points toward a more balanced position: AI can support inclusion when it is embedded in human-centered, UDL-oriented, rights-based systems; it can undermine inclusion when it is deployed as a shortcut.

Overall, the reviewed studies support a cautiously constructive interpretation. AI has real potential to expand accessibility in higher education, especially when it supports multimodal learning, individualized feedback, flexible expression, communication access, and student autonomy. At the same time, the literature shows that these benefits are fragile. They depend on design choices, data quality, institutional policies, teacher preparation, student training, and mechanisms for accountability. For deaf students and Libras users in Brazil, the stakes are even higher because accessibility is inseparable from linguistic recognition and cultural participation. Therefore, the future of inclusive AI in Brazilian higher education should not be defined by technological adoption alone, but by the capacity of institutions to govern technology in ways that deepen democracy, participation, and educational justice.

8. Implications for research, Policy, and practice

8.1. Research

Future research should prioritize participatory and longitudinal designs. Studies on Libras-AI should include deaf users, Libras interpreters, deaf educators, and accessibility professionals throughout the research cycle. Researchers should also report outcomes disaggregated by disability type, language, socioeconomic status, race, gender, and digital access whenever ethically possible. The field also needs comparative studies between AI-supported inclusion and existing human support structures, especially in public higher education.

8.2. Policy

Policy frameworks should classify AI systems used in student evaluation, access, admission, monitoring, risk prediction, and support allocation as high-risk educational technologies. Brazilian regulation should require accessibility validation, algorithmic impact assessment, privacy analysis, human oversight, and mechanisms for contesting AI-mediated decisions. For deaf students, any AI tool affecting communication access should be evaluated in relation to Libras and not only to written or spoken Portuguese.

8.3. Practice

Higher education institutions should adopt AI tools only through accessibility-aware procurement processes. Implementation should include UDL-based faculty development, student AI literacy programs, clear guidance on acceptable use, accessibility testing with disabled students, and ongoing monitoring of outcomes. Institutions should also avoid replacing human interpreters, accessibility staff, and pedagogical support with AI systems that have not been validated with the communities they claim to serve.

9. Limitations

This review has limitations. First, it is a narrative review and does not include a PRISMA flow diagram, formal risk-of-bias scoring, or meta-analysis. Second, the evidence base is heterogeneous, combining peer-reviewed studies, policy documents, conceptual articles, and practice reports. Third, several AI tools and policy frameworks are changing rapidly, which means that some evidence may become outdated quickly. Fourth, the inclusion of Brazil-based studies by members of the authorship team strengthens contextual relevance but also requires reflexive caution. These studies were therefore interpreted as part of a broader evidence landscape rather than as definitive evidence. Finally, the review is limited by the scarcity of empirical studies centered on deaf students, Libras, and Brazilian higher education.

10. Conclusion

Artificial intelligence is neither inherently inclusive nor inherently exclusionary. Its impact depends on the conditions under which it is designed, implemented, governed, and evaluated. In higher education, AI can support accessibility, personalization, and participation for students with disabilities when it is integrated through UDL, rights-based policy, institutional responsibility, and community co-design. The same technologies can also amplify exclusion when they are trained on narrow data, deployed without transparency, or treated as substitutes for human support.

The central conclusion of this review is that inclusive AI must be built with the communities it intends to serve. For Brazil, this means that AI in higher education must take Libras, deaf culture, disability rights, data protection, and institutional inequality seriously. The question is not whether AI will enter higher education; it already has. The question is whether higher education will govern AI in ways that expand participation rather than reproduce the exclusions of the past.

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