Discover Artificial Intelligence

Perspective

The ethics of AI at the intersection of transgender identity and neurodivergence

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Abstract
Artificial intelligence systems increasingly mediate decisions in domains from healthcare and education to law enforcement, but they often inherit historical biases. This paper examines how AI can reproduce and even amplify discrimination at the intersection of transgender identity and neurodivergence. Drawing on evidence that transgender individuals exhibit higher rates of neurodivergence (Pasterski et al. in Arch Sex Behav 43:387–393, 2014) and on the historical pathologization of both identities (Conrad and Schneider in Deviance and medicalization: from badness to sickness, Temple University Press, Philadelphia, 1992), I focus on two domains, healthcare and language processing, to illustrate how choices in data collection, model training, and algorithm design can perpetuate harmful biases. I also evaluate restrictive state policies as exemplified by the U.S. executive order "Defending Women…" (Trump Executive Order. Defending women from gender ideology extremism and restoring biological truth to the federal government. 2025a. https://www.whitehouse.gov/Presidential-Actions/2025/01/Defending-Women-From-Gender-Ideology-Extremism-And-Restoring-Biological-Truth-To-The-Federal-Government/) while exploring how regulatory frameworks may complicate efforts toward inclusive AI design. I conclude with technical and policy recommendations intended to promote fairness while acknowledging the potential benefits and risks of AI systems, and suggest avenues for future research.

1 Introduction

Algorithms now mediate an increasing number of crucial decisions, from law enforcement to school admissions, yet these supposedly 'neutral' tools frequently inherit entrenched societal biases[1]. Police departments increasingly use predictive analytics [13], and biases in these datasets can result in disproportionate targeting of marginalized communities. As these systems increasingly influence decisions in critical areas, they risk perpetuating discrimination against marginalized groups. In this paper, I examine how AI systems can encode and exacerbate biases that uniquely affect individuals who are both transgender and neurodivergent. I will use 'transgender identity' to refer to any gender identity that diverges from the sex assigned at birth, encompassing nonbinary and other non-cisnormative experiences. 'Neurodivergence' will refer to cognitive variations, such as autism, ADHD, and other conditions that deviate from neurotypical norms. A growing body of research suggests that transgender individuals may exhibit higher rates of neurodivergence than the general population [47]. This intersection is not coincidental but reflects shared experiences of medicalization and

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pathologization that have historically marginalized these groups [18]. Because these identities often intersect, biases that affect either group can compound. This intersectional perspective reveals systemic flaws that may remain hidden if we treat each identity category in isolation. By investigating these overlapping identities together, I illustrate how AI technologies, from diagnostic algorithms in healthcare to natural language processing models used for content moderation, can inadvertently reproduce complex, intersectional biases.

In the U.S., recent executive orders and state-level restrictions on gender-affirming care present a helpful backdrop for examining how policy influences AI bias. However, variations in regional legal structures and cultural norms may influence how bias is reflected in AI systems developed and used there. For example, countries such as Peru [27], Argentina [5], Malta [55], Denmark [22], and the United Kingdom [69] have implemented varying approaches to gender recognition that challenge or complement the U.S. model, and these differences will likely impact the nature and extent of bias within AI as developed and used in these different areas.

To provide a focused and in-depth analysis, I narrow my discussion to two domains: healthcare and language processing, including an evaluation of text-to-image generations. These sectors were selected because they offer clear illustrations of how technical choices in data collection, model training, and algorithm design can produce compounded biases for transgender and neurodivergent individuals. In healthcare, for instance, diagnostic decision-support systems and insurance approval algorithms may misinterpret or pathologize conditions common among these populations. Similarly, language processing systems, such as content moderation tools, can misclassify reclaimed terminology or culturally specific expressions, effectively silencing marginalized voices. However, the general points about bias made within these domains may apply to other domains more generally.

The remaining sections of this paper are organized as follows. Section 2 details the relevant concepts of transgender identity and neurodivergence, emphasizing elements directly related to AI bias and introducing alternative models of disability beyond the traditional medical and social dichotomy. Section 3 presents a detailed technical analysis of how bias manifests in AI systems within the selected domains. Section 4 offers concrete recommendations for mitigating these biases through improved data practices, technical interventions, and policy frameworks. Finally, Sect. 5 concludes with a discussion of future research directions and the broader implications for developing equitable AI systems.

2 Background on transgender identity and neurodivergence

Understanding how AI systems propagate bias requires a clear account of transgender identity and neurodivergence, especially those aspects that influence data collection, model training, and algorithmic decision-making.

2.1 Transgender identity

Transgender identity refers to the lived experience of having a gender identity that does not align with the sex assigned at birth. This category includes individuals who identify as transgender, nonbinary, agender, or in other ways that deviate from a strictly cisnormative framework [17]. In many societies, transgender individuals face systemic discrimination, from misclassification on official documents and restricted access to gender-affirming healthcare [33] to accusations of pedophilia merely on the basis of being transgender [68]. These challenges have direct implications for AI systems. For example, facial recognition technologies often rely on datasets built around binary gender categories, leading to misclassification or exclusion of transgender and nonbinary individuals [54]. Similarly, administrative systems that require legal names or government-issued identifications may not accommodate name changes or nontraditional naming practices, such as for neurodivergent individuals who identify as systems [52], thereby reinforcing cycles of marginalization [38]. These misclassifications have direct repercussions for algorithmic design.

State and other administrative regulations on identity and categorization of minority groups have had wide-reaching consequences. At present, more than half of states in the U.S. have laws in place restricting gender-affirming care [16], and an executive order was issued declaring that there are two genders, determined at birth by biological characteristics [63]. Opponents of gender-affirming care may label it experimental or harmful, particularly for minors [70]. However, research shows that withholding gender-affirming care significantly increases rates of suicidality, depression, and self-harm among trans youth, while receiving gender-affirming interventions correlates with improved mental health outcomes [25]. Thus, restricting access not only infringes upon personal autonomy but also poses measurable public health risks.

2.2 Neurodivergence

Neurodivergence encompasses cognitive variations that differ from what is traditionally considered neurotypical, including autism spectrum disorder, attention deficit hyperactivity disorder, and other conditions [15]. Historically, neurodivergent individuals have been subjected to a medical model that emphasizes "normalization" and pathologizes differences. This medical model of neurodivergence focuses on therapies aimed at encouraging conformance to social norms, often failing to appreciate the value of neurodivergent experiences and aiming instead to reduce deviations from the norm [50]. Mild deviations from neurotypical functioning are often diagnosed as mental health disorders, with various conditions and their expressions falling under the umbrella of neurodivergence, including autism. Categorizing neurodivergent individuals as mentally disordered has profound psychological impacts, as this categorization in general may result in adverse outcomes such as demoralization [37]. Socially, neurodivergent individuals face discrimination in various other domains, including employment [36] and education [67]. Such stigma can easily be embedded into training sets used by AI healthcare tools.

2.3 General intersectional considerations in AI bias

Both transgender identity and neurodivergence were historically pathologized through medical and psychiatric frameworks that sought to "cure" or "normalize" individuals who deviated from societal norms [18]. Medical authority was used to enforce both neurotypical and heterocisgender conformity, as the same kinds of medical institutions that performed lobotomies on neurodivergent individuals also administered conversion therapies to LGBTQ + people. These parallel histories of medicalization continue to influence contemporary technological systems, including AI, which often encode assumptions about "normal" behavior, cognition, and identity derived from these historical medical models. As Hamraie and Fritsch [31] argue in their 'Crip Technoscience Manifesto,' the development of technologies has long been shaped by normative assumptions about both ability and gender, leading to designs that privilege certain ways of being while marking others as deviant or in need of correction. Because medical professionals labeled these groups as deviant for decades, the underlying data in medical records and public datasets still reflect those biases [18]. Understanding these connected histories helps explain why current AI systems often perpetuate similar patterns of exclusion and normalization at the intersection of transgender and neurodivergent identities.

While the traditional medical and social models of disability remain influential, many scholars and disabled activists argue for frameworks that avoid the extremes of "cure or ignore." For example, the biopsychosocial model integrates biological, psychological, and social factors to capture the complexity of how conditions and diverse neurology interact with society [4]. Such approaches resonate with the affirmation model, which emphasizes pride, identity, and personal agency over pathology, championing the idea that neurodivergent individuals do not need to "normalize" their behaviors to achieve dignity and inclusion [61].

In the context of AI bias, these alternative frameworks suggest that algorithmic design should accommodate neurological and gender diversity rather than forcing trans neurodivergent individuals to adapt to rigid norms. Failing to do so perpetuates ableist and cisnormative standards [59], especially when AI-driven systems treat any deviation from a "typical" dataset as problematic. By consciously building on relational or biopsychosocial insights, developers and policymakers can create AI tools that better reflect the realities of trans and neurodivergent lives.

Some individuals who would benefit from gender-affirming care may avoid seeking treatment out of fear of stigma and discrimination on the basis of gender identity [34] or on the basis of having a psychological disorder [42]. Moreover, the two can be conflated. For example, symptoms associated with gender dysphoria and obsessive compulsive disorder (OCD), characterized by distressing and unwanted repetitive intrusive thoughts or compulsions, have in some cases been conflated by patients' families such that gender dysphoria was not taken seriously [1], and it is important to prevent such issues from creeping into AI systems.

Existing critiques of AI systems point out the problems with AI operationalizing identity, such as the work of Scheuerman, Paul, and Brubaker [53] and Hamidi, Scheuerman, and Branham [30]. They argue that facial analysis technologies misclassify and exclude transgender and non-binary individuals due to systemic biases in AI that may similarly marginalize neurodivergent individuals [8]. Scheuerman and colleagues [54] offered an analysis of race and gender categorization in image databases for facial analysis, which reveals how such categories are often treated as fixed and 'obvious', failing to recognize their significant complexities and contributing to the systemic exclusion of marginalized groups. Moreover, given that such categorizations are not apparent for some minority members based on facial or voice analysis [49], they may face 'unwarranted scrutiny' from AI systems [48]. Similar remarks can be made for categorizing individuals who are disabled [8], which includes many neurodivergent individuals. For example, Mack and colleagues [40] demonstrate that there is a bias in the representation of disabled individuals in text-to-image AI, and others [28] caution against designs that impose neurotypical norms rather than fostering inclusivity and autonomy more generally. In general, much of the recent literature shows how neurodivergent and transgender individuals are not being treated as equals with respect to their unique needs and goals in many domains of AI development, and how it ought to be developed beyond helping those with such differences conform to neurotypical, cisgender standards.

2.4 Global perspectives on gender recognition

While this paper focuses largely on the United States, where current policy (e.g., the 2025 Executive Order) can assume a rigid, binary definition of gender, many other regions adopt alternative approaches that can inform more inclusive AI designs. In Argentina, for instance, the *Ley de Identidad de Género* respects self-determination, allowing individuals to legally affirm their gender without requiring medical procedures [5]. Similarly, Malta's Gender Identity, Gender Expression, and Sex Characteristics Act provides a framework that similarly prioritizes bodily autonomy and reduces bureaucratic hurdles [55]. Meanwhile, the United Kingdom's ongoing debates around the Gender Recognition Act continue to reveal tensions between state-administered processes and authentic self-expression [69].

The more inclusive legal frameworks hint at how different policy contexts might mitigate bias in AI systems, whereas more restrictive frameworks exacerbate it. Specifically, this analysis of these examples suggests that more flexible legal definitions of gender, anchored in self-identification rather than strictly binary categories, may decrease the chance of AI systems inheriting exclusionary norms. When gender data is collected in a manner that respects diverse identities, developers can train models that better reflect real-world variation, thereby reducing systematic misclassification and harm. In the next section, I explore how AI systems in healthcare and language processing can inadvertently replicate these harmful patterns.

3 Discrimination in AI at the intersection of transgender identity and neurodivergence

Healthcare and language processing represent especially urgent and illustrative focal points for examining AI bias at the intersection of transgender identity and neurodivergence. Healthcare decisions have immediate life-and-death consequences for marginalized communities: from access to gender-affirming treatments to mental health support, biased algorithms risk denying or misdiagnosing the very care on which transgender and neurodivergent individuals rely. Meanwhile, language underpins basic communication, social belonging, and administrative tasks; when AI-based moderation or NLP tools misclassify expressions of trans or neurodivergent identity as "harmful," marginalized voices may be silenced or penalized in online spaces and beyond. These two domains also embody broader, recurrent patterns of algorithmic discrimination that appear across areas such as education, policing, or employment, making them particularly powerful case studies. Moreover, because both transgender and neurodivergent identities have historically been pathologized within medical frameworks, analyzing healthcare systems showcases how seemingly "objective" technologies can perpetuate or amplify these biases. Likewise, language-processing systems reveal how societal stigmas are codified in training data—especially when certain community terminologies are censored or misrepresented. By focusing on healthcare and language, this paper explores some of the critical stakes of AI bias in these domains, and also demonstrates how targeted technical and policy reforms can alleviate harm in other domains.

3.1 Healthcare

AI is increasingly used in healthcare for tasks such as diagnostic decision support, treatment recommendation, insurance claim processing, and telehealth services. However, the design of these systems often relies on historical data that predominantly reflect cisgender and neurotypical populations, leading to several specific biases. Bias in these systems can begin with unrepresentative data collection, where historically marginalized groups appear in small numbers or are mislabeled. During preprocessing, insensitive feature engineering can flatten complex gender identities into binary labels or overlook neurodivergent speech patterns. Without robust fairness metrics at the training and evaluation stages, the final model frequently inherits these biases and applies them at scale.

For instance, diagnostic and decision-support systems may be trained on datasets that underrepresent transgender and neurodivergent individuals. This underrepresentation can result in misdiagnoses or inappropriate treatment recommendations, as algorithms may fail to recognize the unique physiological or behavioral patterns of these groups [21]. Similarly, voice recognition systems used in telehealth applications might misinterpret the speech patterns of transgender individuals or neurodivergent patients, thereby "outing" or excluding them from essential services [58]. For example, such misinterpretation could result in denial of telehealth sessions, effectively shutting out vulnerable patients. Additionally, insurance and coverage algorithms that rely on historical claims data may learn to associate certain treatments, such as gender-affirming care or neurodivergence-related support, with higher risk, thus perpetuating cycles of denial and marginalization [32]. Moreover, there have been documented cases where transgender individuals have been denied access to non-healthcare related services because their appearance did not match outdated documentation [33], and there is the possibility of such issues arising in healthcare. These examples illustrate how inadequate representation in the data and rigid algorithmic assumptions can lead to systematic discrimination in healthcare AI.

Despite these risks, AI also holds promise for improving healthcare access and outcomes for transgender and neurodivergent communities when properly designed and implemented. For instance, AI-driven telehealth platforms have shown potential in increasing access to gender-affirming care, particularly in rural or underserved areas [57]. Community health workers can use AI-enabled tools to locate trans-friendly providers by analyzing patient feedback data [34], thus reducing the documented barriers that transgender individuals face in finding affirming care. Similarly, AI-based voice training technologies, which help trans individuals align vocal presentation with gender identity, are being explored for broader, community-led implementations [11]. These community-informed approaches demonstrate the potential for AI to become a proactive ally rather than an instrument of marginalization. To succeed, developers must actively incorporate trans and neurodivergent perspectives in the design and training phases, avoiding the cisnormative or neurotypical biases that can plague these technologies.

However, healthcare is only one domain where algorithmic bias impacts trans and neurodivergent populations. In the following subsection, we see how similar issues around training data and cultural assumptions emerge in language processing, from content moderation to text-to-image generation.

3.2 Language processing

Language-based AI systems, including content moderation tools, chatbots, and natural language processing (NLP) models, also risk amplifying discrimination through subtle, yet systematic, biases. Many NLP systems are built on word embeddings that capture statistical associations from large datasets. When training data reflect societal prejudices, these embeddings can erroneously associate reclaimed or community-specific terminology with negative sentiments [12]. For example, expressions that transgender or neurodivergent communities use as markers of identity may be misclassified as hate speech or inappropriate content by automated moderation systems [23][2], despite the fact that some of these terms are crucial for self-expression and activism amongst some groups. Transformer-based models that drive content moderation may rely too heavily on superficial lexical cues, leading to the unjust censorship of benign or even positive expressions and further silencing marginalized voices. Systems that integrate language with other modalities, such as images, can further these biases in other ways, reinforcing misclassifications and exclusions [28].

3.2.1 Bias in text-to-image generation

Recent experiments using a popular text-to-image generator provide a concrete example of how AI systems encode and amplify bias against transgender and neurodivergent communities [45]. As analyzed using OpenAI 01 [44], when prompted with "cisgender neurotypical," the DeepAI [19] system consistently produced neutral, photorealistic portraits with conventional backdrops, often resembling stock photography. By contrast, prompts such as "transgender neurodivergent" yielded stylized, sometimes hypersexualized, violent, or surreal visuals, frequently featuring anatomically exposed brains, body modifications, or other dramatic elements. In certain cases, the platform refused to generate images altogether, flagging identity-related terms like "transsexual" or other, sometimes reclaimed terms such as "fag" as unsafe content.

This discrepancy suggests that the model's underlying training data and content moderation policies treat "cisgender neurotypical" as the normative default while associating transgender and neurodivergent identities with more extreme or exotic imagery, or blocking them outright. The original image datasets, and the assumptions baked into them, appear to reinforce sensationalist views of trans and neurodivergent bodies. The result is an overemphasis on sensationalized

[2] The author of the present paper was a data annotator for Dorn (2024).

or pathological depictions, echoing historical tendencies to medicalize and fetishize these identities [18]. Much like the language-based content moderation errors noted above, these biased outputs risk further marginalizing transgender neurodivergent individuals by perpetuating stereotypes rather than providing balanced representation. Consequently, text-to-image generation serves as yet another domain where technical design decisions, both in training data selection and in filtering heuristics, can inadvertently codify discriminatory assumptions about intersecting identities.

The classification of certain terms as "unsafe" points to more general issues related to bias in AI safety mechanisms. While content filters aim to prevent harmful uses of AI, their blanket prohibition of terms like "transsexual" can be problematic, especially given such terms' legitimate use within the community. Recent work on "jailbreaking", techniques to bypass AI safety measures, has demonstrated that these restrictions are often superficial and inconsistent [9]. For instance, users can often circumvent filters through simple modifications like creative spelling or contextual reframing, raising questions about the effectiveness and purpose of such restrictions. More concerning is how these safety mechanisms may disproportionately impact marginalized communities while failing to address underlying harmful uses. Current AI safety measures often reflect an overly simplistic understanding of the potential of such language to be used in a negative way that fails to distinguish between malicious use and legitimate community discourse. This pattern mirrors historical content moderation issues documented by Gillespie [26], where platform governance has consistently struggled to accommodate linguistic reclamation by marginalized groups.

3.3 A note on other domains

While the examples above focus on healthcare and language processing, similar biases are likely to occur in other contexts such as workplace evaluation, education, and emergency response technologies. Due to space constraints and a focus on depth in technical analysis, these additional domains are discussed only briefly here. Future research should extend this analysis to fully explore the ways in which AI-driven discrimination manifests across a broader array of social systems. For example, AI-based admissions or discipline systems in schools may penalize neurodivergent behaviors as "disruptive" and fail to account for trans students' unique social stressors [20]. Similarly, predictive analytics that flags "at-risk" students can overlook or misclassify transgender neurodivergent learners if the training set lacks representation [2]. Hiring and promotion algorithms risk inheriting historical biases, disproportionately screening out transgender or neurodivergent candidates [36, 51].

In contexts such as robotic teams being deployed after emergencies to rescue victims, when efficiency can be a matter of life and death, avoiding bias to maximize efficiency and success rates is crucial [7]. Consider a situation in which the brain activity of a transgender neurodivergent human member of a human–robot search and rescue team was being monitored and affecting the behavior of the human–robot team [46]. If the algorithm was developed on an insufficiently diverse data pool, and differences in brain function are not accounted for, then efficiency may not be optimized, and in turn, more lives may be lost than would have been the case with AI without cisgender neurotypical biases. Moreover, there are other kinds of possible bias in algorithms resulting in life-or-death outcomes, such as which lives to prioritize in these search-and-rescue missions, or which persons to target in military or police operations. Even in matters that are not immediately life-threatening, such as housing, or even the development of recreational uses of technology [59], bias deserves attention so that inequality more generally is not perpetuated by AI. Thus, much of the same or similar bias in AI discussed by the present paper within the domains of healthcare and language processing are found elsewhere,any domain reliant on incomplete or biased datasets risks replicating such discrimination.

3.4 Summarizing key biases

Below, Table 1 illustrates how specific AI subdomains can manifest different biases against transgender, neurodivergent, and especially trans neurodivergent individuals. The columns detail the typical bias mechanisms and unique community impacts.

3.5 Incorporating global legal contexts

As discussed in Sect. 2.4, global differences in gender recognition policies shape how AI systems register and respond to identity data. AI developers in more progressive legal settings are better positioned to create inclusive systems, whereas those in restrictive environments face additional hurdles. Systems trained primarily on U.S.-based datasets may assume binary gender categories or require certain legal documents, inadvertently marginalizing those whose home

Table 1 Bias against transgender neurodivergent individuals in different AI subdomains

AI subdomain	Potential bias mechanism	Impact on trans individuals	Impact on neuro- divergent Individuals	Intersectional impact (Trans + ND)
Healthcare diagnostics	Training data predominantly reflects cisgender and neurotypical populations; algorithms treat deviations as anomalies	May result in misdiagnoses or failure to recognize needs for gender-affirming care [21]	ND traits can be misread as pathology; symptom overlap (e.g., OCD vs. gender dysphoria) can lead to incorrect treatment or stigma [1]	Compounded misclassifications: e.g., attributing trans-related distress solely to ND conditions, or vice versa, leading to inadequate care
Telehealth & voice recognition	Voice analysis tools trained on "typical" voices often fail to accommodate trans pitch ranges or ND speech patterns	Automated voice identity checks may misgender or "flag" trans individuals for suspected fraud; can hinder telehealth access [33, 58]	ND speech patterns (monotone, echolalia, or other distinct features) may be misread as "robotic" or fraudulent, limiting the user's access to telehealth services	Trans ND folks face heightened risk of being locked out if both voice pitch and speech patterns deviate from model norms, exacerbating misclassification and denial of service
NLP & content moderation	Keyword filters block or flag reclaimed slurs and identity-related terms (e.g., "transsexual"	Moderation systems may censor trans terminology, especially reclaimed language, effectively silencing community-specific expressions [23]	Slang or self-referential ND terms get flagged as harmful speech, limiting ND communities' ability to discuss their experiences [12]	Double censorship: intersectional conversations containing both trans- and ND-related reclaimed language face higher rates of take-down or silence
Text-to-image generation	Training data associates "trans" or "neurodivergent" prompts with sexualized, surreal, or unsafe content	Prompts referencing trans identities often yield hypersexualized or fetishized images, or get blocked outright (echoing pathologizing stereotypes)	Terms like "neurodivergent" or "neurospicy" may yield grotesque or violent imagery, reinforcing stigma around ND bodies and minds	Intersectional prompts ("trans neurodivergent") can amplify both sexualized and "freakish" depictions, intensifying misrepresentation and erasure (cf. image experiments)
Facial analysis & verification	Strict gender classification categories trained on binary data; ND behaviors (facial expressions, eye contact) are read as "atypical."	Trans faces are often misclassified or flagged as inconsistent with ID photos, leading to denial of access to apps or services [33]	ND individuals may break typical gaze patterns or facial expressions, triggering misreadings of emotion or identity in face-tracking systems [28]	Trans ND users experience errors on both gender and expression axes, e.g., "mismatched" face data plus unusual affect result in repeated system rejections or flags

jurisdictions affirm self-identification without rigid criteria [5, 55]. This discrepancy can be especially detrimental for trans individuals who are also neurodivergent, as their experiences often diverge from mainstream medical or administrative frameworks. Without accommodating more expansive legal and cultural conceptions of gender, technologies such as AI risk assessment tools, content moderation filters, or healthcare triage algorithms may systematically under-serve or misclassify intersectional populations.

4 Evaluating proposed solutions

Addressing bias in AI systems that disproportionately affects transgender and neurodivergent communities requires a coordinated strategy blending technical innovation, inclusive data governance, and thoughtful policy. A crucial first step involves reconsidering how data are collected and labeled. AI models inevitably reflect the biases embedded in their training datasets, so adopting inclusive data collection practices [17], AI [3] is vital to ensure that the diversity of trans and neurodivergent identities is accurately represented. Such practices may include sampling that captures a wide range of gender identities and cognitive profiles, as well as direct collaboration with community members during annotation to preserve reclaimed terminology and culturally specific expressions [23]. In line with calls for responsible data stewardship [6, 65], any project gathering sensitive demographic information should implement strict privacy measures, such as anonymization or differential privacy, to guard against potential misuse by state or private actors.

Beyond data collection, rethinking model architectures is also necessary. Many existing algorithms measure success through aggregate accuracy alone, but intersectional fairness metrics [24] can help identify hidden discrepancies across subgroups, including those defined by overlapping gender and neurodivergence. Methods like adversarial debiasing and reweighting can proactively address these discrepancies at the training stage, and counterfactual fairness testing can clarify whether altering sensitive attributes (e.g., transgender vs. cisgender, neurodivergent vs. neurotypical) leads to unjustified shifts in outcomes [56]. Documenting these design choices through "model cards" [41] further enhances transparency, helping external auditors and stakeholders spot potential blind spots and contextualize the model's intended uses, limitations, and performance across different demographic groups [14].

Finally, transparent deployment and continuous user feedback are essential to refine and sustain fairness over time. Clear records of data provenance, model assumptions, and performance metrics enable third-party audits, a practice strongly recommended by scholars advocating for public accountability in AI development [3]. Meanwhile, user-centric reporting channels empower transgender and neurodivergent individuals to report instances of bias or misclassification in real time [10]. By integrating these community-driven insights into ongoing iteration and maintenance cycles [39], developers can address emerging problems swiftly and ensure the system evolves alongside community needs. When implemented together, inclusive data practices, intersectional fairness strategies, and continuous feedback loops can help align AI models with the values of equity and respect for all users, particularly those marginalized at the intersection of multiple social minority groups.

4.1 Recommendations within and beyond broader policy context

Although technical fixes exist, their effectiveness depends on a supportive legal environment. Federal- and state-level policies, such as the 2025 Executive Order, demonstrate the power of government mandates to either support or undermine inclusive AI design. By enforcing a biological, binary definition of sex [63], the order circumscribes how AI researchers and developers can legally gather and label data about transgender people. In many U.S. states, previous anti-trans policies from the first-term Trump administration complicated or prevented efforts to expand data fields or adopt flexible identity categories [70], making it even more difficult for developers to capture the full variation of gender identities in training datasets. In ideal circumstances, developers would be not only free but incentivized to aim for more inclusive designs so that such identities can be recognized by AI, but an organization receiving state funding actually may be restricted by any overly restrictive official framework adopted by said state.[3]

However, trans individuals who are also neurodivergent may experience an added layer of exclusion under such policies. If mental health conditions or cognitive traits are similarly treated as less-than, pathologized, or closely regulated

[3] 'I do not wish to answer' as a third category in a binary system is better than no third option, but does not capture all of the other possibilities and is thus inadequate for data-collection purposes. But such considerations align with proposals to include diverse developers and datasets, as well as calls for including minority perspectives when enacting policies which restrict such practices.

[18], well-intentioned AI data practices may be hamstrung by legal frameworks that both deny certain forms of gender recognition and regard neurodivergence primarily through a deficit model (such as discussed by [50]). Consider Peru, for example, where being transgender has been labeled a mental disorder [27]. In these scenarios, developers required to conform to state regulations lack both legal permission and practical guidelines for creating data categories and algorithms that recognize and affirm these identities.

Eliminating Diversity, Equity, and Inclusion programs cut in another 2025 Executive Order 'Ending Radical and Wasteful Government DEI Programs…' [64] will also negatively impact the opportunities available to minority members. Many corporate and governmental organizations have established DEI initiatives to address recruitment, retention, and accommodation strategies for neurodivergent employees [36]. If these offices are shut down or severely restricted, the progress made in inclusive hiring, flexible work environments, and accommodations could be reversed, making it more difficult for neurodivergent talent—particularly those facing added marginalization from being trans—to gain or keep employment. DEI offices often act as the internal advocates for intersectional trainings. For trans individuals on the autism spectrum, for example, an effective DEI department can push for both pronoun flexibility and sensory-friendly workplaces. Without these initiatives, the burden of self-advocacy falls disproportionately on individuals who are already marginalized.

With fewer resources supporting trans and neurodivergent student programs, the data that AI developers use (e.g., educational performance metrics, accommodation success rates) becomes even more skewed toward neurotypical, cisgender norms. If institutional knowledge about marginalized identities is lost due to DEI office closures, AI systems are less likely to be designed or audited by people with expertise in intersectional issues—leading to narrower definitions of "typical" behavior that exclude trans neurodivergent perspectives. When the Department of Education and other civil-rights enforcement bodies lose power or vanish, private companies are under less pressure to ensure algorithmic fairness, whether in admissions tools, scholarship allocation platforms, or special education diagnostics. This undermines accountability for biased outcomes.

For instance, under the constraints of the U.S.'s executive orders' strict regulations, clinics or insurers using AI-based eligibility filters may exclude both the unique needs of trans people and crucial accommodations for neurodivergent communication or behavior. Implementing privacy safeguards (such as anonymization or differential privacy) and intersectional fairness checks can mitigate these effects, but if the policy itself prohibits such demographic labeling, even robust design strategies encounter systemic limits. For instance, imagine developers creating a telehealth platform in a state that mandates only binary sex categories on patient intake forms. Even if these developers wish to add a 'nonbinary' field to better serve trans neurodivergent patients, the law could force them to omit it. As a result, diagnostic algorithms trained on these intake forms perpetuate erasure of and support for some individuals, compounding health disparities.

Accordingly, advocacy groups and professional associations that have been active in gender-affirming care, such as Queer in AI, Queer in Robotics [35], and The Trevor Project [62], might collaborate with neurodivergent-led groups to push for inclusive data definitions and ethical review boards that acknowledge intersectional identities. In fact, this push for intersectional focus is expressed by Korpan and colleagues [35]. Where the policy environment is more flexible, as in Argentina's self-determination law [5] or Malta's Gender Identity Act [55], such cooperative efforts can more easily thrive, signaling that policy context may be a primary gatekeeper of AI's ability to serve, rather than misclassify, marginalized populations.

Ultimately, though the 2025 Executive Order 'Defending Women' is particularly problematic for transgender identity, its ripple effects also touch broader domains where minority statuses are easily overlooked or misread as pathology. Hence, meaningful reform requires both technical and legal interventions, with an eye toward ensuring that so-called protective laws do not exclude the very identities which should be protected by their expressed aims.

4.2 Practical constraints and ethical considerations

The more specific solutions outlined above, such as inclusive data collection, user feedback loops, and intersectional debiasing algorithms, are necessary steps to take toward more equitable AI, but the specific details of implementation will require context-specific evaluations. For instance, collecting more data on gender identity or neurodivergent traits can illuminate biases but also comes with issues involving informed consent and data protection. Such initiatives must align with ethical guidelines that safeguard autonomy and privacy, echoing principle-based frameworks commonly used in biomedical ethics [4] and AI governance [17]. In addition, even robustly engineered AI systems can underperform if implemented within institutions that retain entrenched biases. True inclusivity hinges on ongoing engagement, continuous monitoring, and readiness to recalibrate when unintended harms surface. Thus, these recommendations should be understood as preliminary,more empirical studies are needed to confirm their applicability across varied cultural, legal, and technical contexts.

Inclusive assessment practices can distinguish between neurodivergence, gender dysphoria, and other diagnoses or conditions without pathologizing them. This would in theory be more respectful of these individuals' autonomy, and minimize the harm which comes from treating them as being flawed and in need of changing to be closer to the relevant norm. For example, clinics, especially those specializing in transgender healthcare, can employ multidisciplinary teams to ensure comprehensive evaluations and appropriate care without stigmatizing, changing, or 'curing' fundamental aspects of who they are, when these differences are not in themselves harmful to oneself or others.

When considering how to address AI bias against transgender and neurodivergent individuals, one promising approach is to center the design practices already developed by trans and nonbinary communities themselves. As Haimson et al. [29] demonstrated in their work on "Designing Trans Technology," when transgender people are directly involved in technology design processes, novel solutions emerge that better serve their needs. Rather than trying to retrofit existing AI systems to accommodate gender diversity, starting from trans and nonbinary users' actual practices and needs leads to fundamentally different design choices.

For example, trans communities have developed sophisticated practices around privacy, identity documentation, and information sharing born from necessity and survival [66]. These practices could inform how AI systems handle sensitive personal information and identity verification. Similarly, many trans people have expertise in navigating multiple contexts where different names, pronouns, or gender presentations may be necessary for safety, which could improve how AI systems handle identity across contexts.

Additionally, as Spiel et al. [60] note in their work on "Patching Gender," nonbinary people's lived experiences of moving beyond binary categorizations could provide more informed approaches to how AI systems classify and process identity data. Rather than forcing users into rigid categories, systems could be designed with the flexibility and contextual awareness that trans and nonbinary people already practice in their daily lives.

Ideally, we will progress beyond simply making existing AI systems "trans-inclusive" or "neurodivergent-inclusive" and instead use different ways of knowing and navigating the world to fundamentally reshape how we design AI systems, particularly for users who are both transgender and neurodivergent. As Wyers [71] argues, centering marginalized users in design processes not only serves those specific populations better but can lead to novel solutions that benefit all users through more flexible, contextual, and human-centered approaches.

4.3 Potential risks of data misuse

Efforts to gather more data on transgender and neurodivergent populations, while well-intentioned, can inadvertently expose these groups to heightened vulnerability [12, 23]. In jurisdictions where legal protections are weak or political climates are hostile to LGBTQIA + or neurodivergent identities, comprehensive data sets could be repurposed for surveillance or targeted discrimination [43]. As a result, developers and policy makers must incorporate privacy-enhancing technologies (e.g., anonymization, differential privacy) and ensure robust governance structures before collecting or aggregating sensitive information. These safeguards not only help fulfill obligations to do no harm but also bolster public trust, ensuring that marginalized communities feel safe participating in data-driven systems.

5 Concluding remarks

AI systems can reproduce and even amplify biases against individuals at the intersection of transgender identity and neurodivergence. By focusing on healthcare and language processing, I have shown how technical design choices, from data collection and annotation to model training and deployment, contribute to systemic discrimination. In healthcare, biased diagnostic algorithms and insurance eligibility systems may lead to misdiagnoses and unjust denials of care, while language processing systems risk censoring reclaimed terminology and marginalizing transgender and neurodivergent voices. These technical challenges are compounded by recent policy developments, such as executive orders enforcing a rigid, binary conception of sex [63] or eliminating DEI initiatives [64], which may further exclude transgender identities from AI datasets and applications in the United States.

These considerations suggest the need for inclusive data practices, the integration of intersectional fairness metrics, and the establishment of transparent deployment and feedback mechanisms. These interventions are essential for mitigating bias in AI systems and ensuring that technology serves all segments of society equitably. At the same time, critical engagement with current policy shows the broader challenges of designing inclusive AI in a landscape where political mandates may conflict with best practices for fairness and inclusion. Ultimately, without parallel reforms in legal frameworks and a commitment to intersectional inclusion, even the most advanced technical measures risk being undermined by structural constraints.

Moving forward, future research should not only refine these technical solutions but also investigate the long-term impacts of restrictive policies on AI development and deployment. Longitudinal studies and interdisciplinary approaches will be key to understanding and remedying the systemic biases embedded in my technological infrastructures. Ultimately, this work calls for both immediate technical interventions and sustained policy advocacy; achieving fairness in AI requires a shift in how we collect data, frame policy, and involve marginalized communities in every stage of development.

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Declarations

Competing interests The authors declare no competing interests.

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