TOWARD RESPONSIBLE ASR FOR AFRICAN AMERICAN ENGLISH SPEAKERS:

A SCOPING REVIEW OF BIAS AND EQUITY IN SPEECH TECHNOLOGY

Jay L. Cunningham, Adinawa Adjagbodjou, Jeffrey Basoah, Jainaba Jawara, Kowe Kadoma, Aaleyah Lewis

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HOW ARE BIAS AND EQUITY IN ASR FOR AFRICAN AMERICAN ENGLISH SPEAKERS DISCUSSED ACROSS HCI, ML/NLP, AND SOCIOLINGUISTICS?

BACKGROUND

The Problem: Bias in ASR for African American English

- **AAE Underrepresentation & Bias in ASR:** Most speech datasets don't include enough AAE speech. This makes systems blind to the richness and variation of AAE. These disparities reflect long-standing language ideologies that privilege "standard" English while stigmatizing minoritized varieties, erasing linguistic ideology.
- **Evaluation Gaps:** NLP practitioners typically report overall accuracy numbers without breaking down results by dialect. This masks the disparities AAE speakers experience and ignores the social costs of errors.
- **Real-World Harms:** AAE speakers face mis-recognition in ASR systems when applying for jobs, accessing healthcare, or using educational tools.
- **Lack of cross-disciplinary engagement:** Most existing work on ASR fairness is siloed within ML/NLP, focusing narrowly on technical fixes. HCI scholarship foregrounds UX methods, while sociolinguistics brings crucial insights into linguistic ideologies. Yet, these domains rarely intersect, limiting holistic solutions to ASR equity (Ngueajio & Washington, 2022; Hanna et al., 2020).

METHODS: PRISMA-SCR

- Sources: ACM Digital Library, IEEE Xplore, ACL Anthology, Linguistics and Language Behavior Abstracts (LLBA), plus arXiv, PNAS, Frontiers.
- Corpus: 72 papers retrieved. **44 peer-reviewed papers (ML/NLP: 31; HCI: 11; Linguistics: 2) analyzed**
- Process: 1,800+ search terms expanded via ResearchRabbit; systematic filtering

Analysis

- 5 reviewers, conducted iterative open coding until consensus met; intercoder agreement (κ = 0.82).

KEY FINDINGS

What Did We Learn? 5 Recurring Themes

1. **Understanding Harms:** Researchers are documenting harms AAE speakers face when ASR misinterprets their speech—from everyday frustrations to perpetuating stereotypes and reinforcing systemic inequalities. Bias in ASR is framed not just as error, but as socio-technical harm (trust erosion, miscommunication, surveillance risks).

2. **Data Practices:** Persistent underrepresentation, annotation bias, and lack of dialect-sensitive datasets. Fair ASR begins with fair data. Most corpora underrepresent AAE, and when present, they're often stripped of cultural richness through narrow sampling or biased annotations.

3. **Methods/Theory:** Limited cross-disciplinary dialogue; sociolinguistic insights underutilized in ML/HCI. as the field pushes for frameworks that recognize AAE as a legitimate, rule-governed variety of English, yet many ML practices still treat it as "noise" that is underprioritized.

4. **Design Recommendations:** There are signs of progress—such as calls for dialect-aware training and more transparent reporting—but these efforts remain fragmented, often detached from the communities most affected. Researchers urge principles of participatory design, reflexivity, dataset sovereignty, but most are small-scale and not institutionalized.

CONTRIBUTIONS

Moving Beyond Quick Fixes

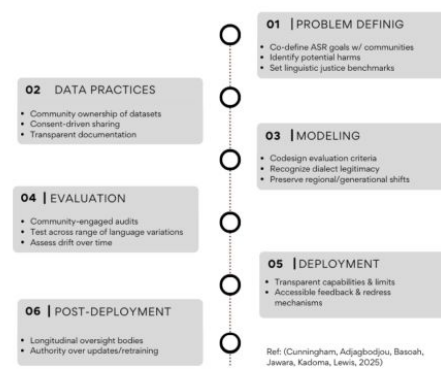
Our study argues that the field has been stuck in a loop of technical patchwork solutions. To really move forward, we need to rethink ASR as a governance problem as much as a technical one. That's why we propose a *Governance-Centered ASR Lifecycle Framework*— as a **socio-technical framework that embeds community agency, participatory oversight, and institutional accountability across all stages of ASR system development**, from problem framing and data collection to evaluation, deployment, and post-deployment auditing.

This framework identifies participatory checkpoints across six stages:

1) Problem Definition
2) Data Sourcing
3) Model Training
4) Evaluation
5) Deployment
6) Post-Deployment Governance

GOVERNANCE-CENTERED ASR LIFECYCLE

Governance-Centered ASR Lifecycle



Emerged gap: lack of governance-oriented interventions → led to Governance-Centered ASR

Why governance-centered approaches remain underexplored?

- Disciplinary silos: ML/NLP, HCI, and sociolinguistics rarely engage holistically.
- Infrastructure barriers: Proprietary datasets and black-box models block transparency.
- Incentive mis-alignment: Academia/industry reward technical novelty over participatory integrity.

How GC-ASR-L(F) can be applied:

- Community Engagement: Involve AAE speakers from the start. Let them help define what "fair" performance looks like and what harms matter most.
- Data Governance: Treat AAE speech data as something to be stewarded, not extracted. This means consent, sovereignty, and equitable compensation.
- Model Design: Build dialect-aware training and culturally competent annotation practices into the heart of development.
- Evaluation: Go beyond one-size-fits-all accuracy. Report performance by dialect and create metrics that reflect lived realities of harm.
- Deployment & Monitoring: Don't stop at launch. Keep auditing systems, incorporate community feedback, and be accountable for failures.
- Policy & Regulation: Align ASR systems with civil rights protections and AI policy frameworks to ensure they support—not undermine—equity.

CONCLUSION

This scoping review highlights persistent inequities in ASR for AAE speakers, revealing gaps across data, modeling, evaluation, and governance. We propose a governance-centered lifecycle framework in ASR development. **Moving forward, interdisciplinary collaboration is essential to build speech technologies that are not only accurate, but also just and inclusive.**

PLEASE SEE PAMPHLET FOR MORE DETAILS | Koenecke, A., et al. (2020); Mengesha, Z., et al. (2021); Wenzel, E., & Kaufman, J. (2023); Green, L. (2002); Rickford, J. (1999); Bird, S. (2024); Ngueajio, M. K., & Washington, G. (2022); Cunningham, J. L., et al. (2024); Hanna, A., et al. (2020); Rosa, J., & Flores, N. (2017).