

# Computational audits combat disparities in recognition

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## Authors

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- **Ariel A. Hippen\***

 [0000-0001-9336-6543](#) ·  [arielah](#) ·  [ariel\\_hippen](#)

Department of Systems Pharmacology and Translational Therapeutics, Perelman School of Medicine, University of Pennsylvania · Funded by The Gordon and Betty Moore Foundation (GBMF 4552)

- **Natalie R. Davidson\***

 [0000-0002-1745-8072](#) ·  [nrosed](#) ·  [n\\_rose\\_d](#)

University of Colorado School of Medicine, Aurora, Colorado, United States of America; Center for Health AI · Funded by The Gordon and Betty Moore Foundation (GBMF 4552)

- **Casey S. Greene**

 [0000-0001-8713-9213](#) ·  [cgreene](#) ·  [GreeneScientist](#)

University of Colorado School of Medicine, Aurora, Colorado, United States of America; Center for Health AI · Funded by The Gordon and Betty Moore Foundation (GBMF 4552)

- **\* denotes co-first authorship. Order determined by simultaneous rolls of d20s over a video call.**

Recognition by peers and the general public can greatly affect the trajectory of a scientist's career. Any recognition—inclusion of one's name in print as an expert, an invited lecture, or an award—paves the way to future accolades. Regardless of an individual's merit, biases can skew which scientists are recognized. This is exemplified in a recent study of disparities in scientific journalism, which found that individuals with names that are predicted to be of East Asian origin were under-quoted and under-mentioned [1]. Regular monitoring of recognition practices can combat this by identifying overlooked groups and creating opportunities to hold the recognizing body accountable.

Auditing efforts can help reduce disparities. For instance, several journalists found that self-audits of gender-based representation in their articles helped them approach parity [2,3]. In award recognition, an audit of the International Society for Computational Biology (ISCB) honorees revealed significant under-representation of people with predicted East Asian name origins and over-representation of US-affiliated scientists. After this study was publicized, ISCB's following honorees had the highest mean predicted probability of having an East Asian name of any previous year, and the nominating committee inducted their first China-based ISCB Fellow [4].

Ideally, audits of representation would only use self-reported gender, ethnicity, and other identifications [5]. While this may be possible prospectively, surveying is impractical for large groups and often impossible retrospectively [6]. In contrast, computationally-derived predictions allow for large-scale audits with as broad a scope as needed. Numerous tools exist to algorithmically infer gender, nationality, and ethnicity using the feature most likely to be present in datasets: an individual's name [7,8].

Prediction models are not a panacea, however; several factors limit both their accuracy at recapitulating self-reported information and their ability to address the underlying motivating questions of diversity audits. For instance, gender associations of a given name can vary by culture, potentially biasing gender predictions where additional information is not available [9]. Also, most gender prediction models are trained on binary gender labels, the use of which systematically overlooks and conceptually erases the representation and contributions of transgender, non-binary, and intersex individuals [10].

Proxy predictions of ethnicity via name origin are more difficult still; choosing categories to probabilistically predict on is non-trivial and difficult to discretize. Furthermore, there is no one-to-one mapping between having a name from a linguistic group and belonging to a minoritized or underrepresented group. Colonialism, immigration, and structural racism have affected both linguistic histories and inclusion or exclusion from scientific communities in complex ways that are nearly impossible to parse from names alone. For instance, classifiers are usually unable to distinguish if names of Hispanic origin come from the Iberian Peninsula or from Latin America [4]. If a target and background population had identical probabilistic proportions of Hispanic names, but the target group primarily consisted of Iberian individuals, underrepresentation of Latin American scientists would go unnoticed in an exclusively name-based analysis.

Recognizing the aforementioned shortcomings, we propose the following recommendations for the creation and deployment of automated auditing tools: 1. *Transparency*. Publicly provide all tools, code, and data used in the analysis. This enables public scrutiny to those being audited and those whose data are used. For confidential data, provide de-identified or aggregated data.

2. *Individuals know best*. Self-identified demographic information should always be used in preference to algorithmic predictions.
3. *Aggregates only*. Audit results should not affect individuals. The gender and ethnicity of an individual are not for an algorithm to decide nor are they the focus of an audit. Analyses must focus on aggregate estimations and any intermediary individual predictions should not be used externally. In addition, analysts must be mindful of hidden subpopulations that may be obscured during aggregation.
4. *Inform the public*. While internal audits can help institutions reflect, researchers should inform the community of identified disparities. This should include a discussion of any caveats associated with the analyses performed (e.g., a binarization of gender) and the ethical implications of such choices.

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