Evaluating Algorithmic Approaches to Uncover Racial, Ethnic, and Gender Disparities in Scientific Authorship

Yimeng Song, PhD, Nabarun Dasgupta, PhD, MPH, and Michelle L. Bell, PhD

To explore the capabilities of race/ethnicity and gender prediction algorithms in uncovering patterns of authorship distribution in scientific paper submissions to a major peer-reviewed scientific journal (*AJPH*), we analyzed 17 667 manuscript submissions from the United States between 2013 and 2022. We used machine-learning algorithms to predict corresponding authors' race/ethnicity (Asian, Black, Hispanic, White) and gender categories based on name-derived probabilities to compare the predictive performance of these algorithms and their impact on disparity analysis.

Predicted White authors dominated submissions and had the highest acceptance rates (21.1%), while predicted Asian authors faced the lowest (14.9%). Predicted women, despite being the majority, had lower acceptance rates (17.9%) than men (20.5%), a trend consistent across most racial/ethnic groups. Different algorithms revealed similar disparities but were limited by biases and inaccuracies in predicting race and ethnicity.

Manuscript acceptance rates revealed disparities by race/ethnicity and gender; predicted White and male authors had the highest rates. While machine-learning algorithms can identify such patterns, their limitations necessitate combining them with self-identified demographic data for greater accuracy. (*Am J Public Health*. 2025;115(7):1129–1136. https://doi.org/10.2105/AJPH.2025.308017)

AJPH July 2025, Vol. 115, No. 7

The academic landscape in the United States is shaped by a complex interplay of socioeconomic and cultural factors, including both historical and contemporary issues related to racism and gender bias. These influences are evident in the demographic composition of the scientific community. Data from 2021 reveal significant racial/ethnic disparities among US tenure-track full-time faculty in degree-granting postsecondary institutions, with 5% Hispanic, 6% Black, 12% Asian, and 73% White achieving these coveted positions,[1] compared with being 19%, 14%, 6%, and 56% of the US population, respectively.[2] In addition, women are consistently underrepresented within these groups; in the United States, women constituted 46.7% of full-time faculty in 2018, up from 31.6% in 1991, reflecting significant progress yet still not achieving full parity despite constituting half of the overall adult population.[3] Moreover, research funding disparities, highlighted by 2019 National Science Foundation data, show a 22.7% funding rate for Asian and 26.5% for Black/African American principal investigators, compared with 31.3% for White principal investigators.[4] Along with disparities in faculty positions and funding, systematic biases are also evident in scientific publications,[5] underscoring the need to analyze authorship patterns for insights into inequities affecting academic visibility and representation.

While numerous studies have documented gender disparities in academic authorship, fewer have addressed racial/ethnic disparities. For example, studies have shown that women face significant barriers in publication and citation rates.[6–10] In 6 leading medical journals, female authorship grew from 5.9% to 29.3% for first authors and from 3.7% to 19.3% for senior authors between 1970 and 2004, yet women consistently lag behind their male counterparts.[6] Furthermore, female-authored works are cited less often, and men are more likely to engage in self-citation.[7] The COVID-19 pandemic has exacerbated these disparities, highlighting persistent structural challenges.[8–10] Regarding racial/ethnic disparities, research has revealed that Hispanic and Black individuals are underrepresented in doctoral degrees, academic employment, and publications.[11] Black scientists, for instance, have fewer publications and citations, contributing to funding gaps. Other studies have found that non-White scientists experience prolonged review times, receive fewer citations, and are underrepresented on editorial boards.[5,12,13] These patterns underscore systemic barriers limiting diversity in academic achievement and publishing.

The limited availability of data on authors' racial/ethnic identities has long hindered research on the racial/ethnic distribution of authors. While some journals, such as the *American Journal of Public Health* (*AJPH*) and *The BMJ*,[14] have begun collecting self-identified race/ethnicity data, the historical scarcity of such data poses challenges for analyzing trends. Advances in machine-learning algorithms, particularly natural language processing techniques, provide opportunities to estimate authors' race/ethnicity based on their names with increasing accuracy.[15–17] However, these methods have limitations. For instance, name-based prediction algorithms tend to underestimate Black authors while overestimating White authors, introducing biases that require careful validation and application.[18] Furthermore, while informative, no algorithm could predict race/ethnicity based on names with 100% accuracy. A systematic examination of these tools is necessary to better understand their potential and limitations in analyzing authorship disparities.

With this study, we aimed to explore the capabilities of race/ethnicity and gender prediction algorithms in uncovering patterns of authorship distribution. Leveraging manuscript submission data from *AJPH*, we evaluated the strengths and limitations of various machine-learning algorithms and used them to explore 3 key questions: (1) What are the racial/ethnic and gender disparities among authors? (2) What are the racial/ethnic and gender disparities in acceptance rates of submitted manuscripts? and (3) How have these disparities evolved over time?

METHODS

We conducted a multistep analysis to examine disparities in authorship by race/ethnicity and gender using machine-learning prediction algorithms. The following methods detail the data sources, predictive models, and evaluation strategies applied in the study.

Data Sets

We used *AJPH* manuscript submission data from January 1, 2013, to December 31, 2022, to investigate racial/ethnic and gender authorship differences when these variables were not self-identified. Each submission record includes the submission date, authors' names, the corresponding author's institutional affiliation and address (for submissions with multiple authors, only 1 corresponding author's address is provided), manuscript title, and the final decision status ("Accept," "Reject Without Peer Review," "Reject After Peer Review"). Notably, editors have access to the names and institutions of authors during the review process, but reviewers are masked and do not know the authors' identities.

Our analysis focused on corresponding authors and included only submissions from the United States. This was because the race/ethnicity prediction algorithms were trained on US data, and address information was only available for corresponding authors. The data set contains 17 667 unique submission records from the United States, representing 73.7% of all *AJPH* submissions worldwide from 2013 to 2022.

We used the L2 Inc voter registration data set (https://l2-data.com) as ground truth data to evaluate the performance of various race/ethnicity prediction algorithms. The data set, updated in November 2023, includes more than 187.3 million complete records from the 50 US states and the District of Columbia (DC). Each record contains the registrant's last name, first name, address, and self-identified race/ethnicity, categorized as Asian, Black, Hispanic, or White. We did not use the entire data set for the evaluation because of significant variation in the sizes of the L2 data records between states and differing algorithm accuracies across states (Table F, available as a supplement to the online version of this article at https://ajph.org). This data heterogeneity could introduce bias and affect the reliability of our analysis. To address this, we developed a sampling strategy to ensure a more balanced and representative evaluation. Specifically, we first divided the data into 51 regional groups based on the 50 states and DC. For each regional group, we randomly selected 1000 records from each of the 4 racial/ethnic categories, leading to a total of 4000 records per regional group. Each record represented a first–last name combination and associated self-identified racial identity. This process was repeated 5 times, creating 5 separate sample sets, each with a total of 204 000 records.

Race/Ethnicity Prediction Algorithms

We used *pyethnicity* for the main analysis. The *pyethnicity* Python package (https://github.com/CangyuanLi/pyethnicity) was developed using the Bidirectional Long Short-Term Memory (BiLSTM) model and ensemble learning techniques.[17] BiLSTM is a type of recurrent neural network that has demonstrated state-of-the-art performance in many natural language processing tasks.[15] The *pyethnicity* was trained and validated using individuals' first and last names from the L2 voter registration data of all 50 US states.

We also explored 2 other algorithms, *rethnicity* and *predictrace*, for comparison. The *rethnicity* R package (https://github.com/fangzhou-xie/rethnicity), developed using the BiLSTM model,[15] was trained and validated on first and last names from Florida voter registration data. The *predictrace* R package (https://github.com/jacobkap/predictrace) was developed using a probabilistic model based on last names from Census data and a first name data set from Tzioumis.[19]

The racial/ethnic categories considered in this study were Asian, Black, Hispanic, and White, as all the algorithms used could differentiate among these 4 groups. We used the full-name model of each algorithm, taking first and last names as input. The output of the models is the probability of an individual being a particular racial/ethnic category. It is important to note that the algorithms predict the ethnic origin of names, which we use as a proxy for race/ethnicity. In the results, terms such as "White," "Asian," "Black," and "Hispanic" refer to these predicted categories rather than self-identified race/ethnicity.

We used a multiple imputation approach to account for uncertainty in the predicted race/ethnicity of authors. Based on the predicted probabilities generated by the model, we created 10 imputed data sets where each author's race/ethnicity was assigned probabilistically. For example, if the name "Samuel L. Jackson" generated probabilities of Asian: 0.017, Black: 0.890, Hispanic: 0.007, and White: 0.086, the imputation process assigned "Black" in most data sets, but occasionally assigned other groups based on their respective probabilities. Each data set was independently analyzed to calculate submission and acceptance rates for each racial/ethnic group. We aggregated the final results across the data sets and calculated 95% confidence intervals of mean probability to reflect the uncertainty from the imputation process (see "Method for Calculating 95% Confidence Intervals," available as a supplement to the online version of this article at https://ajph.org).

Gender Prediction Algorithm

We classified the gender of authors by using an algorithm by an online platform of Gender API, which had been adopted in our previous work.[7] The algorithm was developed using multiple publicly available government and social network data sources. Based on first name and country-of-origin inputs for each individual, the algorithm generated an estimate of whether the individual was male or female, along with a probability. For example, the input of "Karen" and "United States" provides an estimate of female with estimated 0.99 probability. Gender classifications with probability of less than 50% were categorized by the algorithm as unknown. Similar to race/ethnicity prediction, these predictions rely on name-derived probabilities, which we used as a proxy for gender. In the results, "male" and "female" were used to indicate these predicted classifications. We also adopted the multiple imputation approach described previously to incorporate the uncertainty in gender prediction.

Evaluating Predictive Performance

We used 5 metrics to evaluate and compare the performance of selected algorithms: accuracy, precision, recall, f1-score, and coverage (see "Evaluation Metrics," available as a supplement to the online version of this article at https://ajph.org). All these metrics take values between 0 and 1, with higher values indicating better performance on the corresponding dimension in prediction. We averaged the final score of each metric from the scores of all the 5 sample sets of ground truth data. In addition, we performed a sensitivity analysis on *pyethnicity* predictions to assess how varying probability thresholds impacted acceptance rates for racial/ethnic groups, evaluating the stability and implications of these predictions.

RESULTS

We first analyzed submission proportions and acceptance rates by race/ethnicity and gender of authors using *pyethnicity* and Gender API (Table 1).

TABLE 1— Submission and Acceptance Rates by Race/Ethnicity and Gender for Corresponding US Authors in *AJPH*: 2013–2022

Race/Ethnicity and Gender	Overall Submissions (n = 17 667)		Accepted Submissions (n = 3 352)		Acceptance Rate, % (95% CI)
	No. (95% CI)	% (95% CI)	No. (95% CI)	% (95% CI)	
Race/ethnicity classified as					
Asian	3 955 (3 938, 3 971)	22.38 (22.29, 22.48)	588 (581, 594)	17.53 (17.33, 17.73)	14.86 (14.71, 15.01)
Black	2 494 (2 476, 2 512)	14.12 (14.01, 14.22)	453 (442, 463)	13.50 (13.19, 13.81)	18.14 (17.75, 18.53)
Hispanic	1 573 (1559, 1586)	8.9 (8.82, 8.98)	274 (268, 279)	8.16 (8.01, 8.31)	17.39 (17.08, 17.70)
White	9 646 (9 622, 9 670)	54.6 (54.46, 54.74)	2 038 (2 024, 2 052)	60.81 (60.40, 61.21)	21.13 (20.99, 21.27)
Gender classified as					
Woman	10 142 (10 124 10 160)	57.41 (57.30, 57.51)	1 810 (1 803, 1 817)	54.00 (53.80, 54.20)	17.85 (17.79, 17.90)
Man	7 525 (7 507, 7 543)	42.59 (42.49, 42.70)	1 542 (1 535, 1 549)	46.00 (45.80, 46.20)	20.49 (20.41, 20.57)
Race/ethnicity and gender classified as					
Asian woman	2 333 (2 318, 2 348)	13.21 (13.12, 13.29)	350 (344, 357)	10.45 (10.26, 10.64)	15.01 (14.79, 15.23)
Asian man	1 617 (1 607, 1 628)	9.15 (9.09, 9.22)	239 (234, 244)	7.14 (6.99, 7.28)	14.79 (14.51, 15.07)
Black woman	1 446 (1 434, 1 458)	8.19 (8.12, 8.25)	237 (232, 242)	7.07 (6.93, 7.22)	16.39 (16.10, 16.69)
Black man	1 016 (1 005, 1 027)	5.75 (5.69, 5.81)	202 (193, 212)	6.03 (5.75, 6.31)	19.89 (19.09, 20.69)
Hispanic woman	958 (947, 969)	5.42 (5.36, 5.49)	157 (151, 162)	4.67 (4.52, 4.83)	16.36 (15.80, 16.92)
Hispanic man	615 (607, 624)	3.48 (3.43, 3.53)	112 (108, 116)	3.35 (3.22, 3.47)	18.24 (17.54, 18.93)
White woman	5 419 (5 400, 5 439)	30.68 (30.57, 30.78)	1 074 (1 067, 1 082)	32.05 (31.84, 32.26)	19.82 (19.73, 19.92)
White man	4 261 (4 246, 4 277)	24.12 (24.03, 24.21)	980 (967, 993)	29.23 (28.84, 29.62)	22.99 (22.72, 23.27)

Note. CI = confidence interval. Results classified using *pyethnicity* and Gender API.

Among the 17 667 submissions, 54.6% were authored by individuals classified as White, who had the highest acceptance rate at 21.1%. Asian authors contributed 22.4% of submissions but had the lowest acceptance rate at 14.9%. Black and Hispanic authors, contributing fewer papers, had acceptance rates of 18.1% and 17.4%, respectively.

Gender analysis revealed that women authored 57.4% of submissions but had a lower acceptance rate (17.9%) compared with men (20.5%). An examination of race/ethnicity and gender shows that women submitted more papers than men across all racial/ethnic categories. However, women generally had lower acceptance rates than men, except for Asian women, whose acceptance rate was slightly higher than that of Asian men.

We also categorized rejected submissions as either rejected without peer review or rejected after peer review to detail the pattern of rejection (Table A, available as a supplement to the online version of this article at https://ajph.org). White authors were less likely to have their submissions rejected without review (70.6% of submitted articles) compared with Black (74%), Hispanic (74.2%), and Asian (78%) authors. However, White authors experienced a post–peer review rejection rate of 7.8%, higher than Black (7.5%) and Asian (6.9%) authors.

For annual submissions distribution by race/ethnicity (Figure 1a), there is a very consistent ranking for each year, with most articles being submitted by White authors and the fewest by Hispanic authors. For annual acceptance rates by race/ethnicity (Figure 1b), the general temporal trend shows that White authors consistently had the highest acceptance rates over the 10 years studied, followed by Black authors and Asian authors. In contrast, the acceptance rates for Hispanic authors exhibited greater variability over time, with no consistent trend observed.

Upon repeating our analysis using the *rethnicity* and *predictrace* algorithms, similar patterns of disparity were observed (Tables B and C, available as supplements to the online version of this article at https://ajph.org). White authors continued to contribute the most submissions and had the highest acceptance rates. In contrast, Asian authors, despite submitting the second-highest number of papers,

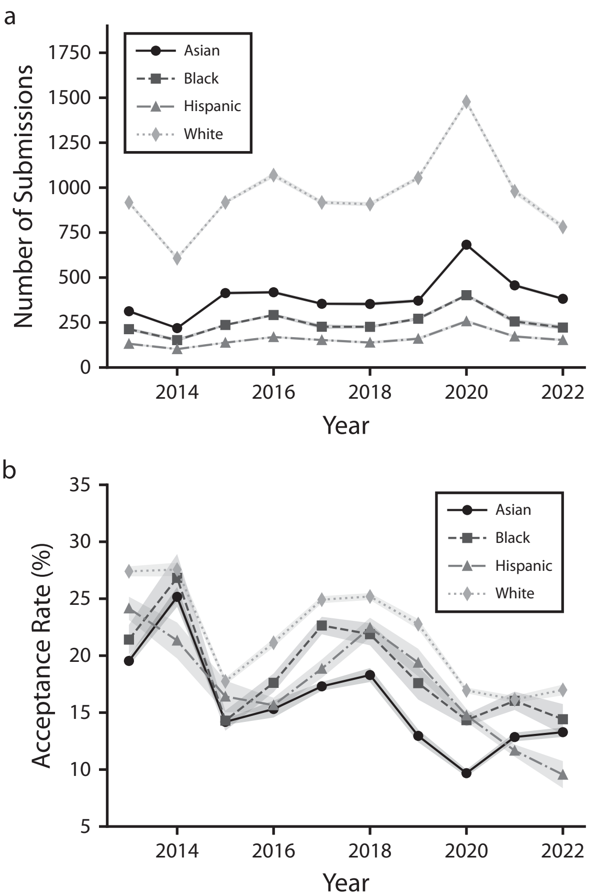

FIGURE 1— Annual (a) Submissions and (b) Acceptance Rates Over Time by Race/Ethnicity for Corresponding US Authors in *AJPH*, With 95% Confidence Intervals: 2013–2022

faced the lowest acceptance rates. Black and Hispanic authors contributed the fewest papers and had lower acceptance rates than White authors. In addition, the trend of women submitting more papers but having lower acceptance rates than men persisted across most racial/ethnic groups using the alternate algorithms.

Algorithm Accuracy

We evaluated race/ethnicity prediction algorithms using L2 data. All algorithms were less effective at predicting Black and White races compared with Asian and Hispanic race/ethnicities (Table D, available as a supplement to the online version of this article at https://ajph.org). *pyethnicity* performed best with high accuracy and precision rates: 0.975 and 0.969, respectively, for Hispanic; 0.952 and 0.967, respectively, for Asian; 0.882 and 0.810, respectively, for Black; and 0.853 and 0.656, respectively, for White. *rethnicity* and *predictrace* showed varying performance across racial/ethnic groups, with lower and less consistent accuracy and precision compared with *pyethnicity*. *predictrace* also had a major issue with coverage, failing to provide predictions for all names.

We found that *pyethnicity* had higher probability scores for its predictions (Figure A, available as a supplement to the online version of this article at https://ajph.org). For the 17 667 submissions analyzed, *pyethnicity* provided 14 466 predictions with probabilities greater than 0.7 and 12 314 with probabilities greater than 0.8, higher than *predictrace* (9644 and 6921) and *rethnicity* (11 901 and 9991). Higher probabilities usually mean higher accuracy and lower uncertainty (Table E, available as a supplement to the online version of this article at https://ajph.org).

We then conducted a sensitivity analysis on *pyethnicity* predictions focusing on probability thresholds and their impact on acceptance rates for various racial/ethnic groups (Table 2). We observed stable acceptance rates for Asian and Hispanic submissions at around 14.4% and 17.0%, respectively. However, as the probability threshold increased, the acceptance rate for White authors rose, while that for Black authors decreased. At a threshold of 0.9 or higher, the acceptance rate for Black submissions was the lowest at 14.5%, while that for White authors increased to 23.5%.

DISCUSSION

Science is strengthened by diversity of thought, and academic publishing is critical to shaping scientific knowledge. However, in this sample of *AJPH* articles, 61 out of every 100 published articles were from White corresponding authors, while only 8 were from Hispanic authors. Academic publishing remains an overwhelmingly White enterprise by volume. We encourage entities in scientific publishing to make serious assessments of how to ameliorate these fundamental inequities.

We drew 3 conclusions from our findings. First, the absolute volume of submissions from racially minoritized authors was considerably lower

TABLE 2— Acceptance Rates of US Authors in *AJPH* by Race/Ethnicity Across Different Probability Thresholds: 2013–2022

Probability ≥	Classified as White, % (95% CI)	Classified as Asian, % (95% CI)	Classified as Black, % (95% CI)	Classified as Hispanic, % (95% CI)
0.27	21.13 (20.99, 21.27)	14.86 (14.71, 15.01)	18.14 (17.75, 18.53)	17.39 (17.08, 17.70)
0.4	21.24 (21.13, 21.35)	14.73 (14.51, 14.94)	18.19 (17.94, 18.44)	17.16 (16.84, 17.49)
0.5	21.34 (21.24, 21.44)	14.81 (14.61, 15.02)	18.02 (17.85, 18.19)	16.96 (16.60, 17.32)
0.6	21.42 (21.34, 21.49)	14.84 (14.69, 14.99)	17.52 (17.14, 17.91)	16.78 (16.44, 17.11)
0.7	21.84 (21.78, 21.90)	14.84 (14.71, 14.96)	17.64 (17.46, 17.82)	17.04 (16.68, 17.40)
0.8	23.72 (23.58, 23.86)	13.97 (13.88, 14.05)	14.59 (14.18, 14.99)	16.93 (16.73, 17.14)
0.9	23.46 (23.34, 23.59)	14.23 (14.12, 14.34)	14.53 (14.22, 14.84)	17.13 (16.91, 17.35)

Note. CI = confidence interval. Results classified using *pyethnicity*.

than their composition in the general population of the United States. This highlights the need for policies that actively encourage submissions from underrepresented, racially minoritized authors and address the racial/ethnic composition of scientists.

Second, the acceptance rates were highest for White authors (21.1%) and lowest for Asian authors (14.9%), showing a considerable gap between the groups. This study is not able to establish root causes for this discrepancy, but our findings warrant further examination. Within academia, upstream mentorship, funding, and research opportunities could have roles to play.

Third, while overall acceptance rates were lower for racially minoritized authors, it is important to note that post–peer review rejection rates were slightly higher for White authors than for Asian and Black authors. Within academic publishing, the longstanding belief has been that science should stand on its own merits, regardless of authorship. This is the core belief justifying masked peer review (historically called “blinded”), where the authors' names are withheld from the reviewers. We concur with others involved in academic publishing in the domains of health[20,21] and psychology[13] who have called for a re-examination of representation by racially minoritized authors in the literature.

Consider, also, that others have found that racially minoritized authors are cited less frequently than White scholars.[5] When less than 40% of published articles are from racially minoritized authors, and those articles are also less frequently cited, the impact of such science is comparatively limited. Taken together, our findings and previous studies suggest that the issues are not merely stochastic; academic social networks, hiring policies, funding, and many other factors may have led to inequities in scientific publishing. We provide 1 quantitative perspective, but clearly, more difficult questions and in-depth research into social and structural determinants are imperative.

These disparities underscore the need to address underlying causes. A recent study found that 77.2% of editors at leading medical and scientific journals were White, 14.9% Asian, 3.8% Hispanic, and 1.1% Black.[22] In addition, faculty of color and women faculty often shoulder more nonresearch duties, such as advising and committee work, which are less recognized in tenure evaluations, potentially hindering career progress and research output.[23,24] They also frequently face racial bias and discrimination, including microaggressions and a lack of colleague support.[25] Minoritized medical school faculty in the United States are promoted at lower rates than their White counterparts, with significantly fewer advancing from assistant or associate professor positions.[26]

We encourage continued review of the existing literature and future research on structural racism and gender discrimination in academia and administrative policies that may perpetuate or mitigate such disparities. Access to financial resources, support networks, and mentorship are likely significant factors affecting these outcomes. The complex dynamics before the submission of a scientific article play a crucial role in determining whose work is submitted and ultimately accepted.

Although our work is one of the few studies to examine racial bias in scientific publishing, we note that it represents only the experience from 1 journal and has inherent limitations. The use of only the corresponding author could also favor White authorship, because corresponding authors tend to have seniority within academic institutions and are often selected as corresponding authors because they have tenure, name recognition, or long-term job stability. In this way, the use of the corresponding author is a proxy for prestige and favored academic positions. Our analysis cannot evaluate the impact of the quality of submitted manuscripts; however, this could also be impacted by systematic inequities, such as unequal access to mentorship, funding, writing and language assistance, or research opportunities.

Our findings showed differences in the performance of the 3 algorithms used for race/ethnicity prediction. *pyethnicity* outperformed *rethnicity* and *predictrace*, achieving higher accuracy and precision, particularly for Asian and Hispanic categories. However, prediction accuracy was lower for Black and White categories across all algorithms, reflecting challenges in accurately classifying these groups. *predictrace* also faced significant coverage issues, failing to provide predictions for some names. These differences highlight the importance of algorithm design, including the quality and diversity of training data, and underscore the need for careful validation to ensure these tools do not amplify existing disparities or perpetuate inequities.

Several limitations of the algorithms could have impacted the observed results. First, all the algorithms were trained using US election data, with accuracy varying across states (Table F, available as a supplement to the online version of this article at https://ajph.org). This variation introduces uncertainty when predicting on a global scale. While we analyzed only US submissions, many authors could be from outside the United States. Second, our data may not capture surname changes from marriage, leading to discrepancies in predicted versus actual racial/ethnic identities, especially for female authors. Third, the race/ethnicity categories used (White, Asian, Black, Hispanic) do not capture other races/ethnicities such as Native American peoples; differences among Native Americans (e.g., Cherokee, Lumbee), Hispanics (e.g., Mexican, Cuban), or Asians (e.g., Indian, Chinese); further cultural and societal differences within these subcategories; or multiracial identities. Similarly, the gender identification algorithm only considers male and female categories, ignoring other gender identities like nonbinary. Furthermore, the similar disparity patterns observed across algorithms may reflect shared biases in their design or training data, such as overrepresentation or underrepresentation of certain groups, which could influence the results.

Our sensitivity analysis further revealed that varying probability thresholds influence the estimated acceptance rates across racial/ethnic groups. Higher thresholds resulted in estimates of a higher acceptance rate for White authors and a lower rate for Black authors, suggesting that acceptance rates for Black authors may be overestimated while those for White authors may be underestimated. These findings underscore the uncertainty in predictions for these groups and highlight the risks of relying solely on algorithmic predictions without addressing their inherent biases.

Despite these limitations, our analysis identified consistent trends. Most submissions came from White authors, who also had the highest acceptance rates. Women, while submitting more papers overall, had lower acceptance rates than men across most racial/ethnic groups. These disparities align with existing literature and underscore systemic inequities in academic publishing.

To address these issues, future studies would benefit from incorporating self-identified data on race/ethnicity and gender. Some journals have begun collecting such data voluntarily, which could improve analysis precision and provide deeper insights into disparities. These efforts, combined with continued refinement of prediction algorithms, are critical for developing strategies to promote equity in scholarly publishing. AJPH

ABOUT THE AUTHORS

Yimeng Song is with the School of the Environment, Yale University, New Haven, CT. Nabarun Dasgupta is with the Gillings School of Global Public Health, University of North Carolina at Chapel Hill. Michelle L. Bell is with the School of the Environment, Yale University, New Haven, CT, and the School of Health Policy and Management, College of Health Sciences, Korea University, Seoul, Republic of Korea.

CORRESPONDENCE

Correspondence should be sent to Yimeng Song, Yale University, School of the Environment, 195 Prospect St, New Haven, CT 06511 (e-mail: yimeng.song@yale.edu). Reprints can be ordered at https://www.ajph.org by clicking the “Reprints” link.

PUBLICATION INFORMATION

Full Citation: Song Y, Dasgupta N, Bell ML. Evaluating algorithmic approaches to uncover racial, ethnic, and gender disparities in scientific authorship. *Am J Public Health*. 2025;115(7):1129–1136.

Acceptance Date: January 2, 2025.

DOI: https://doi.org/10.2105/AJPH.2025.308017

ORCID iD:

Yimeng Song https://orcid.org/0000-0001-9558-1220

CONTRIBUTORS

Y. Song and M. L. Bell originated and developed the study’s concept and hypothesis, conducted the analysis, and contributed to the overall conceptual framework and interpretation of the results. Y. Song, N. Dasgupta, and M. L. Bell contributed to the conclusions and preparation of the article.

ACKNOWLEDGMENTS

We thank Meredith Loui for helping prepare the data set and Alfredo Morabia for valuable insights.

CONFLICTS OF INTEREST

The authors have no conflicts of interest to report.

HUMAN PARTICIPANT PROTECTION

Yale University's institutional review boards approved this project on May 31, 2023 (IRB-2000035422).

REFERENCES

1. National Center for Education Statistics. Characteristics of postsecondary faculty. US Department of Education, Institute of Education Sciences. 2024. Available at: https://nces.ed.gov/programs/coe/indicator/csc. Accessed August 30, 2023.
2. US Census Bureau. Population estimates, July 1, 2023 (V2023). 2023. Available at: https://www.census.gov/quickfacts/fact/table/US/PST045221. Accessed August 30, 2023.
3. Colby G, Fowler C. Data snapshot: IPEDS data on full-time women faculty and faculty of color. American Association of University Professors. 2020. Available at: https://www.aaup.org/news/data-snapshot-full-time-women-faculty-and-faculty-color#.Y_MVrdVByUl. Accessed August 30, 2023.
4. Chen CY, Kahanamoku SS, Tripati A, et al. Systemic racial disparities in funding rates at the National Science Foundation. *eLife.* 2022;11:e83071. https://doi.org/10.7554/eLife.83071
5. Liu F, Rahwan T, AlShebli B. Non-White scientists appear on fewer editorial boards, spend more time under review, and receive fewer citations. *Proc Natl Acad Sci USA.* 2023;120(13):e2215324120. https://doi.org/10.1073/pnas.2215324120
6. Jagsi R, Guancial EA, Worobey CC, et al. The "gender gap" in authorship of academic medical literature—a 35-year perspective. *N Engl J Med.* 2006;355(3):281–287. https://doi.org/10.1056/NEJMsa053910
7. Bell ML, Fong KC. Gender differences in first and corresponding authorship in public health research submissions during the COVID-19 pandemic. *Am J Public Health.* 2021;111(1):159–163. https://doi.org/10.2105/AJPH.2020.305975
8. Bendels MHK, Müller R, Brueggmann D, Groneberg DA. Gender disparities in high-quality research revealed by Nature Index journals. *PLoS One.* 2018;13(1):e0189136. https://doi.org/10.1371/journal.pone.0189136
9. Andersen JP, Schneider JW, Jagsi R, Nielsen MW. Gender variations in citation distributions in medicine are very small and due to self-citation and journal prestige. *eLife.* 2019;8:e45374. https://doi.org/10.7554/eLife.45374
10. King MM, Bergstrom CT, Correll SJ, Jacquet J, West JD. Men set their own cites high: gender and self-citation across fields and over time. *Socius.* 2017;3:2378023117738903. https://doi.org/10.1177/2378023117738903
11. Hopkins AL, Jawitz JW, McCarty C, Goldman A, Basu NB. Disparities in publication patterns by gender, race and ethnicity based on a survey of a random sample of authors. *Scientometrics.* 2013;96(2):515–534. https://doi.org/10.1007/s11192-012-0893-4
12. Ginther DK, Basner J, Jensen U, Schnell J, Kington R, Schaffer WT. Publications as predictors of racial and ethnic differences in NIH research awards. *PLoS One.* 2018;13(11):e0205929. https://doi.org/10.1371/journal.pone.0205929
13. Roberts SO, Bareket-Shavit C, Dollins FA, Goldie PD, Mortenson E. Racial inequality in psychological research: trends of the past and recommendations for the future. *Perspect Psychol Sci.* 2020;15(6):1295–1309. https://doi.org/10.1177/1745691620927709
14. Richards M. BMJ journals collect gender, race, and ethnicity data on submissions. *BMJ.* 2022;379:o2542. https://doi.org/10.1136/bmj.o2542
15. Xie F. rethnicity: An R package for predicting ethnicity from names. *SoftwareX.* 2022;17:100965. https://doi.org/10.1016/j.softx.2021.100965
16. predictrace: Predict the Race and Gender of a Given Name Using Census and Social Security Administration Data. Version 1.7.1. 2023. Available at: https://github.com/jacobkap/predictrace. Accessed August 30, 2023.
17. Li C. Can we trust race prediction? Preprint. Posted online July 17, 2023. arXiv 230708496. https://doi.org/10.48550/arXiv.2307.08496
18. Kozlowski D, Murray DS, Bell A, et al. Avoiding bias when inferring race using name-based approaches. *PLoS One.* 2022;17(3):e0264270. https://doi.org/10.1371/journal.pone.0264270
19. Tzioumis K. Demographic aspects of first names. *Sci Data.* 2018;5(1):180025. https://doi.org/10.1038/sdata.2018.25
20. Watts V. Dismantling racism in scholarly publishing, intentionally and unapologetically. *Health Affairs Forefront.* January 26, 2021. https://doi.org/10.1377/forefront.20210125.666787
21. Boyd RW, Lindo EG, Weeks LD, McLemore MR. On racism: a new standard for publishing on racial health inequities. *Health Affairs Forefront.* July 2, 2020. https://doi.org/10.1377/forefront.20200630.939347
22. Salazar JW, Claytor JD, Habib AR, Guduguntla V, Redberg RF. Gender, race, ethnicity, and sexual orientation of editors at leading medical and scientific journals: a cross-sectional survey. *JAMA Intern Med.* 2021;181(9):1248–1251. https://doi.org/10.1001/jamainternmed.2021.2363
23. Misra J, Lundquist JH, Holmes E, Agiomavritis S. The ivory ceiling of service work. *Academe.* 2011;97(1):22–26.
24. Griffin KA, Reddick RJ. Surveillance and sacrifice: gender differences in the mentoring patterns of Black professors at predominantly White research universities. *Am Educ Res J.* 2011;48(5):1032–1057. https://doi.org/10.3102/0002831211405025
25. Garcia GA, Johnston-Guerrero MP. Challenging the utility of a racial microaggressions framework through a systematic review of racially biased incidents on campus. *J Crit Scholarship Higher Educ Student Aff.* 2015;2(1):48–66.
26. Fang D, Moy E, Colburn L, Hurley J. Racial and ethnic disparities in faculty promotion in academic medicine. *JAMA.* 2000;284(9):1085–1092. https://doi.org/10.1001/jama.284.9.1085