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Non-White scientists appear on fewer editorial boards, spend more time under review, and receive fewer citations

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Disparities continue to pose major challenges in various aspects of science. One such aspect is editorial board composition, which has been shown to exhibit racial and geographical disparities. However, the literature on this subject lacks longitudinal studies quantifying the degree to which the racial composition of editors reflects that of scientists. Other aspects that may exhibit racial disparities include the time spent between the submission and acceptance of a manuscript and the number of citations a paper receives relative to textually similar papers, but these have not been studied to date. To fill this gap, we compile a dataset of 1,000,000 papers published between 2001 and 2020 by six publishers, while identifying the handling editor of each paper. Using this dataset, we show that most countries in Asia, Africa, and South America (where the majority of the population is ethnically non-White) have fewer editors than would be expected based on their share of authorship. Focusing on US-based scientists reveals Black as the most underrepresented race. In terms of acceptance delay, we find, again, that papers from Asia, Africa, and South America spend more time compared to other papers published in the same journal and the same year. Regression analysis of US-based papers reveals that Black authors suffer from the greatest delay. Finally, by analyzing citation rates of US-based papers, we find that Black and Hispanic scientists receive significantly fewer citations compared to White ones doing similar research. Taken together, these findings highlight significant challenges facing non-White scientists.

science of science | scientific careers | race | inequality | peer review

Significance

Empirical evidence suggests that non-White scientists experience various forms of inequality, creating barriers to their entry and participation in academic research. We contribute to this literature by examining disparities in i) editorial board representation, ii) time spent under review, and iii) citation rates. Using a dataset of 1,000,000 papers from six publishers over the past two decades, we find fewer non-White editors than would be expected based on their share of authorship. Moreover, non-White scientists endure longer waiting times between the submission and acceptance of their manuscripts, and upon publication, their papers receive fewer citations than would be expected based on textual similarity. These findings highlight ways through which non-White scientists suffer from inequalities, potentially hindering their academic careers.

The underrepresentation of racial minorities in science is well documented (1–7), but racial disparities in academia go beyond the problem of underrepresentation. Take citations for example. By analyzing the reference lists of papers published in top neuroscience journals, a recent study found that papers with White first and last authors are cited 5.4% more than expected, while those with non-White first and last authors are cited 9.3% less than expected (8). Similarly, scientists of color receive less media coverage. More specifically, it has been shown that East Asian scientists make up less than 7.7% of quotes in nonresearch articles published by the journal Nature, while they constitute 14.3% to 33.6% of all relevant last authorships (9). Racial disparity is also observed in career opportunities. For example, among medical school faculty, underrepresented minorities (including Black, Mexican American, Native Alaskan, Native American, and Puerto Rican) are less likely to be promoted compared to their White counterparts at both assistant and associate professor levels (10). A follow-up study found that there is no longer a racial difference in the promotion rate of associate professors, but Black assistant professors still suffer from having the lowest promotion rates across all specialties and take the longest time before getting promoted (11). Even after being appointed as faculty members, Black and Asian scientists are less likely to receive US NIH grants compared with White scientists (12). Consequently, it is not surprising that names of Celtic/English origin are overrepresented, while names of East Asian origin are underrepresented among honorees such as scientific society fellows or keynote speakers at conferences organized by those societies (13).

Our study contributes to this line of research by examining geographical and racial disparities in three aspects that are closely related to research-active scientists. The first is editorial board composition. Editors are the group of elite decision-makers in science (14) who act as "opinion formers, gatekeepers, and arbiters of disciplinary values" (15). Since editors can exert considerable control over scientific discourse, it is important to identify the underrepresented demographic groups among editors. Past studies on ethnic and racial diversity found that the majority of editorial board members are White in various disciplines (16–20). The unequal representation of nationalities on the editorial boards has also been considered in the literature. In particular, past studies found that editorial boards are dominated by scientists from

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North America and Europe (21–27). *SI Appendix*, Table S1 provides a summary of all studies on ethnic and geographical diversity in editorial boards. However, despite these studies, our knowledge about editorial board diversity remains lacking due to the absence of a longitudinal study comparing the racial composition of the editorial boards of each journal to the racial composition of scientists who publish in that journal.

The second aspect considered in our study is acceptance delay—the number of days between the submission and acceptance of a manuscript. While the peer review process is necessary for scientific rigor, prolonging this process may have a toll on the authors, especially if they are funded for a fixed period of time (as is typically the case with PhD students and postdoctoral researchers) or if they have a deadline after which their performance is evaluated (as is the case with tenure-track faculties) (28). Various paper-related and scientist-related attributes have been found to correlate with the length of the peer review process. For example, papers whose authors are editorial board members, most frequent contributors of the journal, or from high-income countries experience shorter acceptance delays (29). Papers with positive findings also spend significantly shorter time under review compared to those without (30). The personal relationship between an editor and a reviewer may also affect the time line of the peer review process, with the reviewers known personally by the editor being more likely to respond to a review request (31). However, to date, there has been no study that explores the racial and geographical disparities in terms of the acceptance delay of papers.

The third and final aspect is citation rates. Past studies have shown a racial gap in citation rates across disciplines (8, 32, 33). However, all these studies quantify the citation gap while only taking into consideration bibliometric characteristics (e.g., publication year and publication venue as well as the authors' disciplines, affiliations, and academic age), effectively disregarding what is arguably the most important factor that scientists consider when deciding whether to cite a paper or not—the content of that paper. To address this shortcoming, a recent study proposed a method called citational lensing (34), which builds on the tradition of using textual analysis along with citation data to model the spread of knowledge (35, 36). This method allows for quantifying citational distortions while controlling for textual similarities between papers. The authors applied their method to compare citation rates across countries but not across races. One may argue that the citation gap between races can be inferred from the gap between countries, especially since the population in some countries is dominated by a certain race. However, such analysis would not be able to disentangle the effect of the author's race from the effect of the geographical location of their affiliation. To this end, there is a need for a study that examines the racial gap in citation rates based on textual similarity while holding the country constant.

Here, we compile a dataset of more than a million papers between the years 2001 and 2020 in over 500 different journals, handled by nearly 65,000 editors and published by six different publishers, namely, Frontiers, Hindawi, Institute of Electrical and Electronics Engineers (IEEE), Multidisciplinary Digital Publishing Institute (MDPI), Public Library of Science (PLOS), and PNAS, while identifying the handling editor of each paper and identifying the authors' and editors' entries in the Microsoft Academic Graph (MAG) dataset; see Methods for more details. Using this dataset, we are able to chart the racial and geographical disparities in the aforementioned aspects—editorial board composition, acceptance delay, and citation rates—at an unprecedented scale. Taken together, our findings offer a better understanding of the inequalities experienced by non-White scientists, showing that they appear on fewer editorial boards, spend more time under review, and receive fewer citations compared to White scientists doing similar research.

Results

Editorial Board Representation. We start by examining the degree to which the scientists in any given country are represented on editorial boards. To this end, we divide the percentage of editorship by the percentage of authorship from each country, resulting in a national editor-to-author ratio; *Methods* for more details on how this ratio is calculated. As such, the scientists in any given country are overrepresented if the ratio is > 1 and underrepresented if it is <1. Fig. 1*A* shows the editor-to-author ratio for all countries around the globe. As can be seen, the vast majority of countries in Asia, Africa, and South America (where most of the population is ethnically non-White) are underrepresented in editorial boards. Overall, scientists residing in these continents account for 35% of authorship but only 19% of editorship. *SI Appendix*, Table S2 specifies the percentage of authorships and the percentage of editorships from each country. As can be seen, there are countries in which the former percentage is extremely small, e.g., Botswana and Angola, the two main outliers in Africa, account for less than 0.02% of total editors combined. To exclude such countries, Fig. 1*B* focuses on those that have at least 1,000 editors and are statistically significantly overrepresented or underrepresented on editorial boards. Indeed, out of the 16 countries in Africa, Asia, and South America, 13 are underrepresented, with Malaysia, China, and South Korea having less than half the editorships that one would expect based on their percentage of authorships.

So far, these findings reflect the average trend taken over the six publishers and nineteen disciplines that we focus on in our study. Fig. 1*C* analyzes each publisher in isolation, showing that countries in Asia, Africa, and South America are more likely to be underrepresented on the editorial boards of each publisher, with the only exception being PNAS, whose editors are predominantly US based since they are all members of the National Academy of Sciences. The two publishers with the greatest disparities are MDPI and Hindawi, with 93% and 84% of Asian, African, and South American countries being underrepresented on their editorial boards, respectively, while 55% and 80% of North American, European, and Oceanian countries are overrepresented. Moreover, analyzing each discipline separately reveals that the geographical disparity is widespread across all disciplines (Fig. 1*D*). Finally, out of all journals in our dataset, we focus on those who happen to be among the top 20 journals in their respective discipline according to Google Scholar (37). As can be seen in Fig. 1*E*, these journals show little geographical disparities in terms of editorial board representation.

Having examined the representation of different countries in editorial boards, we now examine the representation of different races. Following other works in the literature (13, 32, 38), we infer the scientists' race from their names; *Methods* for more details. To eliminate the above-established confounder—the country in which the scientists are affiliated—we restrict our analysis to those affiliated with US-based institutions. Focusing on a single country may control for additional confounders, e.g., whether English is the authors' working language. Fig. 2*A* shows that White scientists make up 57% of all editors, followed by Asian and Pacific Islander (API) scientists who make up about 40% of all editors, while only 3% and 0.1% of editors are Hispanic and Black, respectively. One possible explanation could

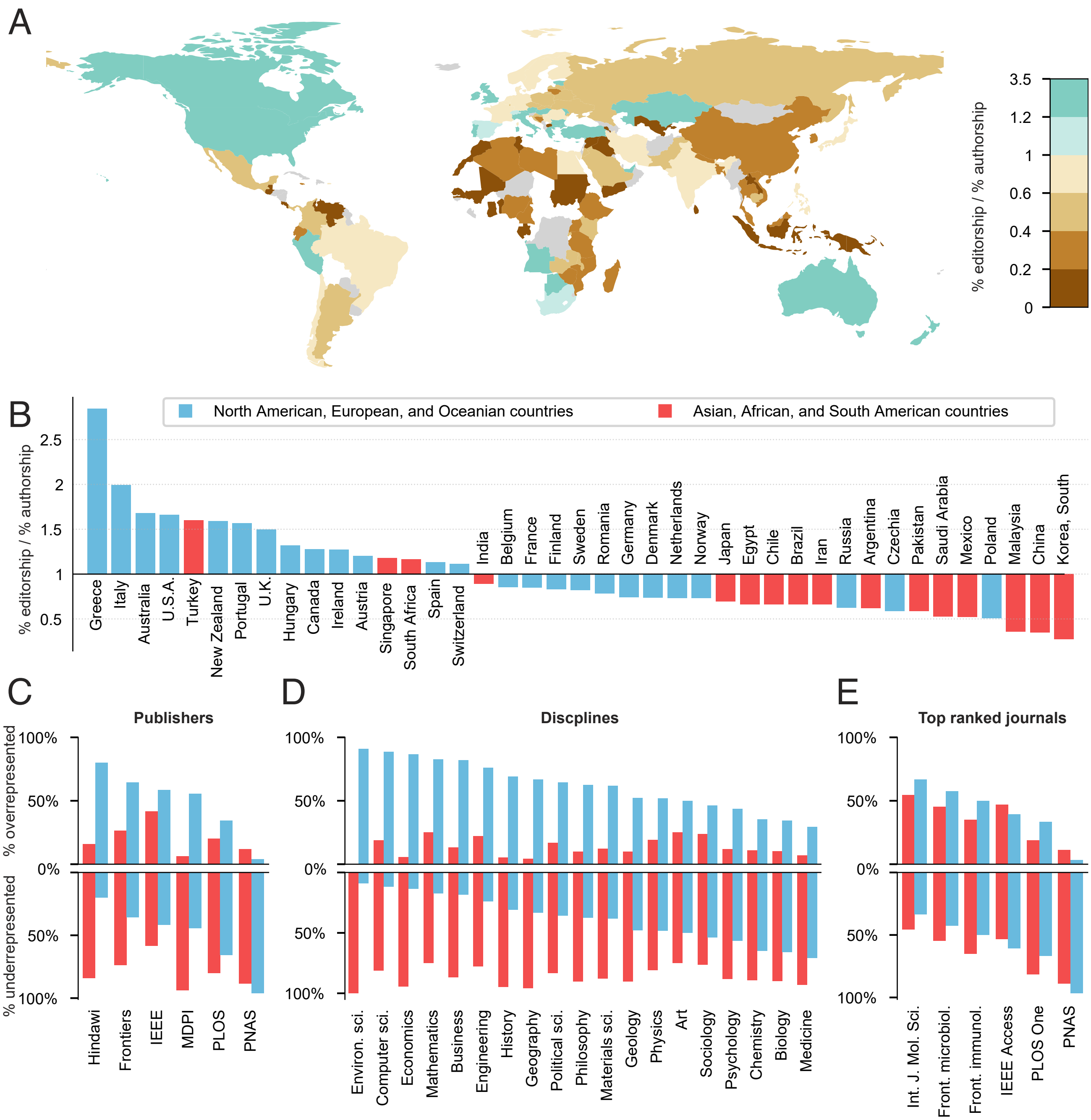

Fig. 1. Representation of countries among editors. For any given country, the editor-to-author ratio is calculated as the percentage of editorship from that country divided by the percentage of authorship from that country. A country is overrepresented among editors if the ratio is >1 and underrepresented if the ratio is <1. (*A*) Editor-to-author ratio for countries around the globe. Here, a country is colored in (light or dark) green if it is significantly overrepresented, in (different shades of) brown if it is significantly underrepresented, and in gray otherwise (Fisher's exact test, $P < 0.001$). The editor-to-author ratios for all countries are divided into five quantile intervals. The interval containing 1 is further subdivided into two disjoint intervals, one consisting of values >1 (assigned a shade of green) and another consisting of values <1 (assigned a shade of brown). Countries for which the percentage of authorship or the percentage of editorship is zero are omitted from the map. (*B*) Editor-to-author ratio of countries that have at least 1,000 editors and are significantly overrepresented or underrepresented in editorial boards; countries in Africa, Asia, and South America are colored in red, while other countries are colored in blue. (*C*) In each publisher, the percentage of countries that are significantly overrepresented (*Upper* panel) and underrepresented (*Lower* panel). (*D*) The same as (*C*) but in each discipline. (*E*) The same as (*C*) but in each top-ranked journal according to Google Scholar.

be the fact there are fewer non-White scientists compared to White ones in the United States. To explore this possibility, we compared the racial distribution of editorship to that of authorship. As shown in Fig. 2 *B–E*, during the first years of the millennium, White scientists were markedly overrepresented, while Hispanic, API, and Black scientists were underrepresented on editorial boards. In the years that followed, the racial gap has been closed for Hispanic scientists and appears to be closing for API scientists. Unfortunately, however, the gap grew even larger for Black scientists.

Next, to determine whether the underrepresentation of non-White scientists occurs in the editorial boards of certain publishers but not in others, we examined the editor-to-author ratio in each publisher separately during the past decade, i.e.,

Fig. 2. Representation of races among editors. This figure focuses on US-based scientists. (*A*) The percentage of White, API, Hispanic, and Black editorships. (*B*) For each year between 2001 and 2020, the percentage of White editorship (solid circles) and White authorship (empty circles). (*C–E*) The same as (*B*) but for API, Hispanic, and Black, respectively. Shaded areas and error bars represent 95% CIs. (*F*) The percentage of White authorship (left panel) and the percentage of White editorship (*Right* panel) in each publisher between the years 2011 and 2020 (inclusive). The number at the center represents the difference between the two panels; a positive number indicates that White editors are overrepresented. (*G–I*) The same as (*F*) but for API, Hispanic, and Black, respectively. (*J*) The same as (*F*) but in each discipline.

from 2011 to 2020. As shown in Fig. 2 *F–I*, White scientists are underrepresented in only one out of the six publishers, API, and Hispanic scientists are underrepresented in four out of the six, while Black scientists are underrepresented across all publishers. When grouping editors into disciplines, we see broadly similar patterns. In particular, White editors are overrepresented in most disciplines (Fig. 2*J*), while API and Hispanic editors are underrepresented in most disciplines, and Black editors are underrepresented in all disciplines (*SI Appendix*, Fig. S1). Even when focusing on journals that are ranked among the top 20 according to Google Scholar, we find that White scientists are overrepresented in four out of the six journals, while Black scientists are underrepresented in all of them (*SI Appendix*, Fig. S2).

Acceptance Delay of Papers. So far, we considered one outcome of interest: the representation of scientists on editorial boards. Let us now consider the second outcome of interest: the acceptance delay of papers. Specifically, acceptance delay is calculated as the number of days between the date on which a paper is received and the date on which it is accepted. Based on this, the relative acceptance delay (RAD) is calculated for any paper p published in journal j in year y as the relative difference between the acceptance delay of p and the average acceptance delay of papers published in j in year y; *Methods* for a formal definition. Let us start by comparing the average RAD across countries. To this end, for any given country, we identify the papers of which the majority of authors are affiliated with an institution in that country and then calculate the average RAD of all those papers.

Fig. 3*A* depicts the average RAD for each country that has at least 500 papers published by the six publishers considered in our study. We can see that countries in Asia, Africa, and South America have higher average RAD compared to other countries. More specifically, out of the 20 countries with the greatest average RAD, 19 are located in the above three continents. These countries are Uganda, Kenya, Bahrain, Nigeria, Bangladesh, Indonesia, Iran, Colombia, Ethiopia, Malaysia, Brazil, Chile, Ghana, Mexico, India, Tunisia, Vietnam, Pakistan, and South Africa, all of which have ethnically non-White majority populations. For the full list of countries and their respective RAD, *SI Appendix*, Table S3. This geographical disparity in RAD has persisted over the past decade (Fig. 3*B*). When restricting our attention to countries that have statistically significantly faster or slower RAD than average, we find that all countries experiencing longer delays are located in Asia, Africa, and South America, with the Netherlands being the only exception; *SI Appendix*, Fig. S3. *SI Appendix*, Figs. S4 and S5 provide the same analysis but for each publisher separately. Similar patterns can be observed for all publishers except IEEE. For a breakdown of geographical disparity in RAD across disciplines, *SI Appendix*, Fig. S6.

Having examined the average RAD across countries, let us now examine it across races. Here, to eliminate the above-established confounder of countries, we restrict our analysis to papers of which all authors have an affiliation based in the United States—a racially heterogeneous country that contributes the largest number of papers in our dataset. This analysis reveals that papers with Black-majority authors experience significantly longer RAD compared to White-, API-, and Hispanic-majority papers (Fig. 3*C*). Examining RAD over time reveals that, for each race, RAD remained stable over the past two decades (Fig. 3*D*), suggesting that Black-majority papers have been consistently spending more time from submission to acceptance compared to other races.

So far in our analysis of RAD, we focused on the authors' race as well as the country in which they are affiliated. Next, we shift our attention to the editors by examining their race and country of affiliation. To this end, for each country that was analyzed in Fig. 3*A*, we divide all the papers produced by that country into two groups: i) those whose handling editor is based in the same country as the majority of authors and ii) those whose handling editor is based in a different country. We found that, for most countries, there are no statistically significant differences in RAD between the two groups (*SI Appendix*, Fig. S7). One possible explanation could be the lack of data, as suggested by the large error bars in *SI Appendix*, Fig. S7 since most countries are not well represented on the editorial boards. However, among the countries that do show significant differences in RAD, apart from Ghana, papers experience a significantly shorter delay when the handling editor and the majority of authors are based in the same country. Next, we focus on the editors' race. As can be seen in Fig. 3*F*, for papers with White-majority authors, we find no evidence that RAD is shorter when handled by a White editor. However, for papers of which the majority of authors are non-White, RAD is shorter by about 10% when the handling editor is non-White. Together, these results suggest that RAD is related to the demographic difference between editors and authors. Alternatively, if papers are classified according to the race of first authors, the result remains qualitatively unchanged, although racial disparity is more pronounced when we classify papers based on the majority race of a paper (*SI Appendix*, Fig. S8). Finally, we incorporate various papers and author characteristics, including the ones examined so far, in an OLS regression where the outcome is the RAD of papers. As shown in *SI Appendix*, Fig. S9, the results provide further evidence that Black authors, as well as authors based in Asia, Africa, and South America, experience longer acceptance delays.

Citational Distortion. Finally, we turn to the third outcome of interest—citational distortion. In particular, we used a recently proposed measure that quantifies how much more (or less) scientists of different cohorts cite one another relative to the pairwise textual similarity between research papers authored by scientists from each cohort; this measure was used in a recent study to analyze regional differences in citational distortion (34). This study showed that Asia and Europe experience moderate citational distortion; Africa, the Middle East, Latin America, and the Caribbean are strongly undercited, while North America and Oceania are strongly overcited across disciplines. We follow the same approach, except that we focus on the four racial groups considered in our study, and restrict our attention to papers of which the majority of authors are affiliated with US-based institutions, thereby eliminating the said confounding effects of countries; *SI Appendix* Note for more details on how citational distortion is quantified. To broaden the scope of this analysis, we focus on all US-majority papers in MAG rather than restricting our attention to the six publishers examined earlier. This, however, means that we cannot use editor-based information in this analysis since such information is not provided by MAG. The result of this analysis is summarized in Fig. 4. As can be seen in Fig. 4*A*, Black and Hispanic scientists have been consistently undercited over the past four decades, while API and White scientists have been consistently overcited relative to what is predicted by textual similarity. Fig. 4 *B*–*E* show that this phenomenon persists across four types of disciplines, namely, i) biomedical, behavioral, and ecological sciences, ii) engineering and computational sciences, iii) physical and mathematical sciences, and iv) social sciences.

Discussion

In this study, we compiled a dataset of more than a million papers between the years 2001 and 2020 in over 500 different journals, handled by nearly 65,000 editors and published by six different publishers, namely, Frontiers, Hindawi, IEEE, MDPI, PLOS, and PNAS, while identifying the handling editor of each paper and identifying the authors' and editors' entries in the Microsoft Academic Graph (MAG) dataset. To our knowledge, this dataset is the largest of its kind to date, capturing information about the handling editor and the time spent under review for a million papers spanning multiple decades, publishers, and disciplines. Using this dataset, we examined three outcomes of interest: the editor-to-author ratio, the time spent between the submission

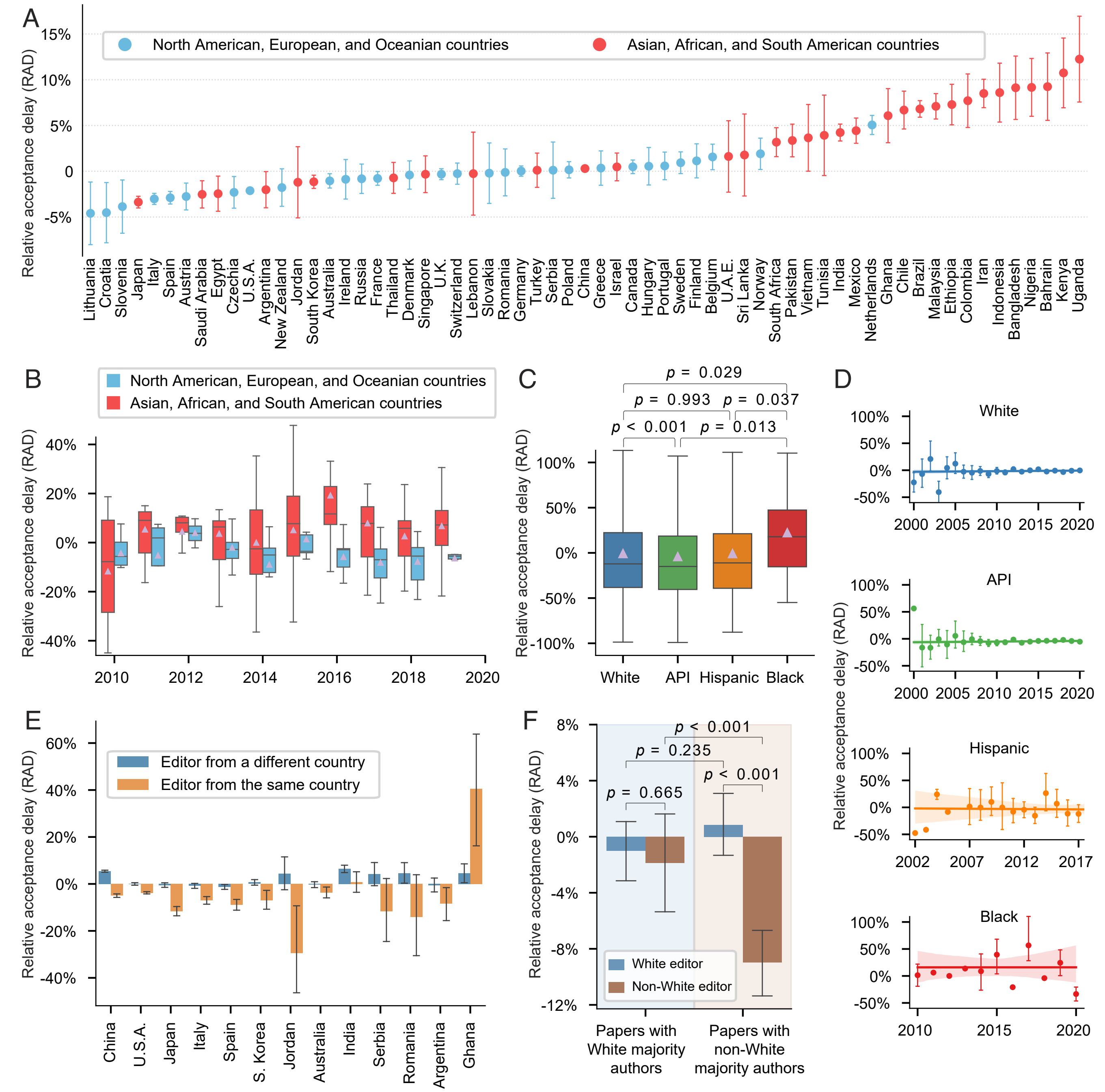

Fig. 3. Relative acceptance delay (RAD). For any paper *p* published in journal *j* in year *y*, the relative acceptance delay (RAD) is calculated as the relative difference between the number of days *p* spent under review and the number of days an average paper published in *j* in year *y* spent under review. (*A*) RAD of each country that has at least 500 papers published by the publishers considered in our study. Countries in Africa, Asia, and South America are colored in red, while other countries are colored in blue. (*B*) RAD distribution over time. (*C*) RAD distribution of papers with White-, API-, Hispanic-, or Black-majority authors; mean values are depicted as triangles; *P* values are calculated using two-sided Welch's *t*-test. (*D*) Average RAD over time for papers with White-, API-, Hispanic-, or Black-majority authors; lines are fitted using the OLS method, while the shaded region represents 95% confidence intervals of the regression estimate. (*E*) RAD of papers handled by editors based in the same country as the authors or based in a different country; here, all countries show a statistically significant difference in RAD between the two groups of papers at the 0.05 level using two-sided Welch's *t*-test. (*F*) RAD of papers handled by editors from the same or a different racial group as the majority of authors; *P* values are calculated using two-sided Welch's *t*-test. In (*A*), (*D*), (*E*), and (*F*), data are presented as mean values ±95% confidence intervals. In (*B*) and (*C*), boxes extend from the lower to upper quartile values, with a horizontal line at the median; whiskers extend to the most extreme values no further than 1.5 times the interquartile range from the box.

and acceptance of a paper, and the number of citations a paper receives relative to textually similar papers.

Our study is not without limitations. First, it only considers six publishers since these were the only ones we could find who specify the handling editor of each paper. Until other publishers make this information publicly available, the extent to which our findings generalize to other publishers remains unknown. Second, we demonstrate that non-White scientists experience disparity following two different approaches: i) analyzing geographical disparity and comparing "White countries" to "non-White countries," i.e., comparing countries with ethnically White majority to those with ethnically non-White majority, and ii) by

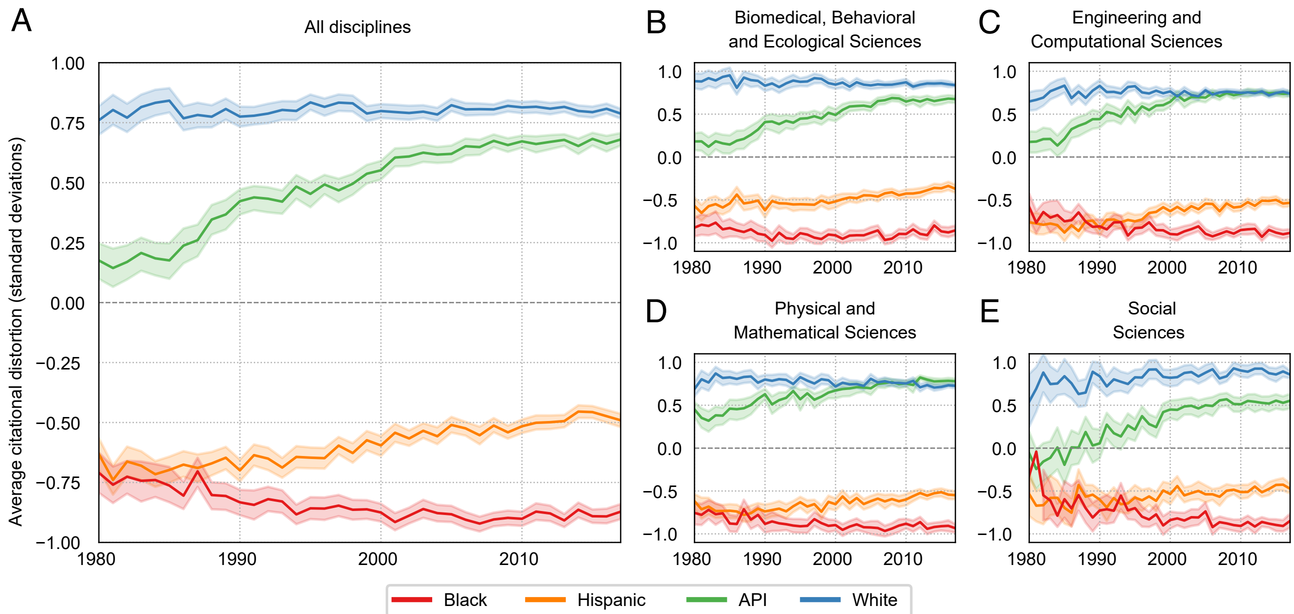

Fig. 4. Racial gap in citation rates based on textual similarity. The average citational distortion experienced by US-based White, API, Hispanic, and Black scientists calculated across disciplines (*A*) in biomedical, behavioral, and ecological sciences (*B*); in engineering and computational sciences (*C*); in physical and mathematical sciences (*D*); and in social sciences (*E*). The citational distortion is measured by comparing the citation rates of textually similar papers. Shaded areas reflect 95% CIs.

analyzing racial disparity while focusing on a single country, namely, the United States. However, neither approach is perfect. The first shows that an average scientist based in a non-White country experiences disparity. Although it could be argued that scientists in non-White countries are themselves more likely to be non-White, there could still be White scientists in such countries. The second approach addresses this limitation by focusing on a country with a racially heterogeneous population and studying racial disparity within that country. Here, we use an algorithmic tool that classifies a scientist's race based on their name. Although this tool is widely used in the social sciences, it is not a perfect classifier. Still, despite their limitations, it is worth noting that two independent approaches reveal similar patterns, suggesting that non-White scientists indeed experience disparity.

More specifically, starting with the first outcome, we compared the editorship rate to the authorship rate from each country, and found that most countries in Asia, Africa, and South America (where the majority of the population is ethnically non-White) are underrepresented among editors. Note that the six top-ranked journals display a more balanced editorial board composition that does not systemically favor editors from North American, European, and Oceanian countries, suggesting that there could be a link between editor representation and the impact of a journal; exploring this link could be a promising future direction. When comparing the racial composition of editors and authors who are based in the United States, we found that Black scientists have been underrepresented on editorial boards across publishers over the past two decades.

Generally speaking, when studying the degree to which different races are overrepresented or underrepresented in any aspect of academia, a fundamental question is to determine the ideal racial composition to aspire to (13). One such composition could be that of members of a specific academic society (17, 18) or that of the population of a specific country (16). In our study, we quantified the racial gap in the editorial board of any given journal using two different benchmarks: i) the composition of authorship in that journal and ii) the authorship composition in a journal's field. Having said that, closing the observed gap should not be taken as the ideal to aspire to as the benchmark itself is likely to have a racial gap due to the documented entry barriers facing scientists of color across disciplines (32). While our work highlighted the racial gap in editorship, more research is needed to identify the policies required to close this gap.

Moving on to the second outcome of interest, we found that papers coming from Asian, African, and South American countries experience longer RAD (relative acceptance delay), i.e., more days between their submission and acceptance compared to papers from other countries published in the same journal and the same year, indicating that ethnically non-White scientists spend on average more time waiting for their manuscripts to be accepted, and this disparity persisted over time. Moreover, we found evidence that papers handled by editors based in the same country as the majority of authors tend to experience shorter RAD. We then turned our attention to authorships coming from the United States and found that Black scientists experience significantly longer acceptance delays compared to White scientists in the United States; this persisted over the past decade.

The additional time Black scientists spend waiting for their submissions to be accepted is alarming but unfortunately not surprising. Black people have already been shown to endure longer waiting times in many aspects of life. For example, during the 2016 US presidential election, residents of entirely Black neighborhoods spent more time waiting at voting stations compared to residents of entirely White neighborhoods (39); longer waiting times for Black voters have also been documented in the 2018 midterm elections (40). Unfortunately, similar observations were made in situations where longer waiting times could mean the difference between life and death. In emergency rooms, for example, Black patients are less likely to be placed into the "Most Urgent" category of the Emergency Severity Index (ESI) (41). Moreover, the time Black patients spend waiting to receive cancer diagnosis is significantly longer than that of White patients both in the United States (42) and the United Kingdom. (43). Our study contributes to this line of this research by showing that Black scientists in the United States suffer from longer delays before their manuscript is accepted for publication. While our study focused on acceptance delay, a future extension could focus on rejection delay, i.e., the number of days between the submission and rejection of a manuscript, to determine whether similar racial disparities can be observed. Unfortunately, however, such a study would require a rejection dataset which is hard to acquire.

As for the third outcome, we showed that Black and Hispanic scientists receive fewer citations than White and API scientists. Crucially, this result is obtained while accounting for the papers' textual similarity using the recently proposed method of citational lensing (34). The same trend is observed across four types of disciplines, namely, i) biomedical, behavioral, and ecological sciences, ii) engineering and computational sciences, iii) physical and mathematical sciences, and iv) social sciences. These findings persisted over the last four decades. The citational gap is particularly alarming for Black scientists since the discrepancy between their actual citation rates and those predicted by textual similarity appears to be increasing over the past decades.

The racial gap in citations means that non-White scientists have lower visibility compared to White scientists doing similar research. This is especially alarming since those with low visibility are less likely to receive grants and awards (44), which, in turn, may lead to even greater disparities in visibility, thereby triggering a Matthew effect (45). More broadly, our three outcomes paint a grim picture in which non-White scientists suffer from inequalities that may hinder their academic careers. These disparities could be linked to non-White scientists receiving less professional respect (46), though more research is needed to confirm this link. Addressing these disparities may require publishers to carry out internal audits to detect and eliminate any disparities in the publication process, from the selection of editorial board members, to the time spent reviewing submissions, to the promotion of published manuscripts. Having said that, the responsibility to take action falls not only on the shoulders of publishers but also on the scientific community as a whole to create an ecosystem without geographical and racial disparities.

Materials and Methods

Editor Data Collection. The six publishers analyzed in our study are the Public Library of Science (PLOS), Frontiers Media S.A. (Frontiers), the Multidisciplinary Digital Publishing Institute (MDPI), Hindawi Publishing Corporation (Hindawi), the Institute of Electrical and Electronics Engineers (IEEE), and the PNAS. We refer to these as publishers since they publish scientific papers, although it should be noted that these are actually four publishers, one academic society (IEEE), and one multidisciplinary journal (PNAS). For IEEE, our study only considers the ten open-access journals that publicize the editor's name and the dates of submission and acceptance. For PNAS, our study only considers the papers that are published since the year 2001 as none of the remaining five publishers existed before 2001. Notice that the publisher PNAS currenlty publishes two journals, namely PNAS and PNAS Nexus. Since the latter journal published its first issue in 2022, while our dataset does not extend beyond 2020, this journal is not included in our analysis. For a breakdown of the number of papers, authors, and editors from each publisher, *SI Appendix*, Table S4. Next, we describe the procedures of collecting information pertaining to the handling editors as well as the dates of submission and acceptance.

PLOS, Frontiers, MDPI, and Hindawi provide full-text corpora of all papers published therein, along with editorial process metadata, enabling us to extract the dates on which papers were received and accepted as well as the names of the handling editors. As for PNAS, although it does not maintain such a corpus of its papers, it has granted us permission to scrape its website. As such, we scrape the web page of each paper, and extract the dates on which the paper was received and accepted, as well as the name of its handling editor. We only considered papers submitted through the direct submission track, which makes up the vast majority of PNAS papers, and excluded from our analysis all communicated papers (a submission track that was discontinued in 2010) as well as all contributed papers (a submission track that only members of the National Academy of Sciences can use). As for IEEE, it neither maintains a full-text corpus of its papers nor does it reply to our request to scrape its website. Therefore, we had to restrict our analysis to the subset of open-access journals whose papers can be downloaded freely and manually collect the information we need, i.e., the dates on which each paper was received and accepted and the name of the handling editor. Similar to the dates and names of handling editors, the affiliation of editors was also extracted from the metadata of papers published by PLOS, Frontiers, PNAS, and IEEE. On the other hand, Hindawi and MDPI only specify this information for currently active editors. As such, we downloaded past versions of the editorial board web pages using the Wayback Machine and then recorded the affiliations of the editors listed in each version. For example, this page lists the current editorial board member of Disease Markers–a journal published by Hindawi–while this page tracks the historical snapshots taken of the same page.

Editor's name and affiliation allow us to identify the bibliometrics data of editors using the Microsoft Academic Graph (MAG)–a dataset that provides publication records of over 200 million scientists (47, 48), and it is widely used by the Science of Science researchers (34, 38, 49–54). More specifically, an editor e affiliated with institute x in year t is considered the same person as a scientist s in MAG, if and only if s is the only one in MAG who has the exact same name as e, and is affiliated with institute x in year t.

Discipline Classification. MAG categorizes papers into 19 top-level disciplines, which are further categorized into lower-level subdisciplines on five different levels. Let D be a high-level discipline, and let d be a lower-level subdiscipline. We write $d \in D$, if and only if d is a child of D. Each paper, p, is associated with a discipline, d, with a confidence score $conf(p, d) \in [0, 1]$. Using this information, we consider a paper p to be in a top-level discipline D with a certain confidence calculated as follows:

$$conf(p, D) = \max_{d \in D} conf(p, d).$$

Based on this, the primary discipline of a paper, p, is computed as follows:

$$\begin{aligned}\mathcal{D}(p) &= {}_{D}\, conf(p, D)\\ &= {}_{D} \max_{d \in D} conf(p, d).\end{aligned}$$

Race Classification. To identify the race of each scientist, we followed the common practice of using computational methods designed specifically to infer an individual's race from their name (13, 32, 38). More specifically, we use *NamePrism* to classify scientists into six different racial groups: Asian/Pacific Islander (API), American Indian/Alaskan Native (AIAN), Black, Hispanic, Two or more races (2PRACE), and White (55). Note that NamePrism is widely used in the social sciences to infer the race or ethnicity of given names (38, 56–64). Since an extremely small number of scientists were classified as either AIAN or 2PRACE, we excluded these two racial groups from our study. Using the classified race of scientists, we classify the papers into racial groups based on the race associated with more than 50% of the authors.

Calculating Editor and Author Representation. When calculating the percentage of authors from a certain country, we count the number of authorships (author–paper pairs) with an affiliation in that country, implying that the same author may be counted multiple times. Similarly, when counting editorship from a certain country, we count the number of papers that were handled by an editor whose affiliation resides in that country, implying that the same editor may be counted multiple times. In other words, we weigh the percentage of authors (and editors) by the number of papers that they produce (or edit). The same applies when measuring racial, instead of geographical, disparity. In Fig. 1 *A* and *B*, we calculate the editor-to-author ratio of a country c as follows:

$$\frac{\%\text{editorship from } c}{\%\text{authorship from } c}.$$

In Fig. 1*C*, we analyze each publisher separately and calculate the editor-to-author ratio of a country c in publisher p as follows:

$$\frac{\%\text{editorship from } c \text{ in } p}{\%\text{authorship from } c \text{ in } p}.$$

Similarly, in Fig. 1*D*, we analyze each discipline separately and calculate the editor-to-author ratio of a country c in discipline d as follows:

$$\frac{\%\text{editorship from } c \text{ in } d}{\%\text{authorship from } c \text{ in } d}.$$

When studying racial, instead of geographical, disparity, we calculate author representation in a similar way. More specifically, in Fig. 2 *F*–*I*, we report the percentage of authorship from race r in each publisher p; in Fig. 2*J* and *SI Appendix*, Fig. S1, we report the percentage of authorships from race r in each discipline d.

The above equations account for cross-publisher and cross-discipline variations in geographical and racial compositions of authorships. As such, for any given journal, perfect representation is achieved when the percentage of editors from each country (or race) matches the percentage of authors who publish in the journal from that country (or race). The underlying intuition is that, if two countries (or races) have the same percentage of authorship in a particular journal, then as far as the journal is concerned, these countries are of equal quality and should therefore be equally represented on its editorial board.

Alternatively, one could argue that perfect representation is achieved when the percentage of editors (from a country or race) matches the percentage of scientists in the journal's discipline (from that country or that race) regardless of how many of them publish in the journal in question. We examined disparity from this perspective in Fig. 1*E*. Here, for every journal that happens to be among the top 20 according to Google Scholar, we calculate the editor-to-author ratio of a country c in journal j as follows:

$$\frac{\%\text{editorship from } c \text{ in } j}{\%\text{authorship from } c \text{ in } j\text{'s discipline}}.$$

To this end, we identify the discipline of each journal as follows. The editorial board composition of IEEE Access is compared against the authorship composition of all Engineering papers. As for the following three journals: International Journal of Molecular Sciences, Frontiers in Immunology, and Frontiers in Microbiology, their editorial board composition is compared against the authorship composition of all biology papers. Finally, since PLOS One and PNAS are multidisciplinary, the representation of editors in these two journals is compared against the authorship baseline pooled across all papers in our dataset.

Calculating Relative Acceptance Delay. The relative acceptance delay (RAD) is calculated for any paper p published in journal j in year y as the relative difference between the acceptance delay of p and the average acceptance delay of papers published in j in year y. Formally, for a paper p published in journal j in year y, the RAD of p equals **1**.

$$\frac{\begin{array}{c}(\text{acceptance delay of } p)- \\ (\text{avg. acceptance delay of all papers published in } j \text{ in } y)\end{array}}{(\text{avg. acceptance delay of all papers published in } j \text{ in } y)} \times 100. \quad [1]$$

Data, Materials, and Software Availability. Anonymized data and computer code required to reproduce the findings have been deposited in Zenodo, https://doi.org/10.5281/zenodo.7058226.

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