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A look at the increasing demographic representation within behavioral medicine

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Abstract Meeting the behavioral medicine research and clinical needs of an increasingly diverse United States population is an issue of national concern. We examine the trends in the demographic representation of the behavioral medicine scientific workforce through an analysis of the training grants funded by National Institutes of Health for the field of behavioral medicine from 1980 to 2018. We report the topics of these training grants, and we depict the demographic representation of the training leaders. We provide the demographic representation of the trainees, and of the first authors of publications reported within those training grants. Finally, we report the topics addressed in these behavioral medicine publications, to determine if topic diversity increased as the behavioral medicine scientific workforce diversified. Visualizations are presented that tell a story of how we have, and have not, advanced representation within the field of behavioral medicine. Best practices for launching future successful behavioral medicine scientists are then presented, to ensure optimal representation and diversification occurs in our workforce, our science, and our delivery of our clinical care.

Keywords Behavioral medicine workforce · Trainees · Training topics · Demographics · Diversity · Representation

Introduction

Increasing the scientific workforce diversity for behavioral medicine is essential to forging our nation's research agenda (Smedley et al., 2004), advising public health policy makers, training future generations of scientists (United States. Congress. Commission on the Advancement of Women Minorities in Science, 2000), and to reducing our nation's health disparities (Smedley et al., 2004). Yet, judging whether or not a scientific field is advancing its demographic representation is a daunting task. Many have declared that we have not yet attained this goal, and so need concerted interventions to amplify our efforts in training a more diverse next generation of scientists (Wilder et al., 2013). Not only will there be honest disagreements about how to assess efforts towards diversification, but the metrics by which to judge advancement in this area are not easily apparent. This publication is an opportunity to describe why representation is important to the field of behavioral medicine, and to describe how our field is faring in advancing the representation of our scientific workforce and of our focus of scientific inquiry.

Why is representation of the behavioral medicine scientific workforce important? Four arguments have been presented. First, the core mission of our scientific field is to improve health behaviors and psychological processes affecting health. To accomplish this mission, we simply

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must understand, study, and incorporate ethnic, cultural, sexual, and countless other nuanced identifications into research (Kazdin, 2016). Both our variables and our outcomes of interest are profoundly influenced by cultural features, and our science doesn't simply suffer, but fails if we merely acknowledge these differences. Second, there is a clash in our clinical practice arena between narrow standardization of best practices, and the need to address complexities that result from ensuring that theories, assessments, processes, and treatments are appropriate for a multicultural population (Rosmarin, 2016). There must be a diverse workforce, representing all sides of this debate to create rich, complex, and productive implementation progress. Third, we have a national health outcome disparity that is indisputable and is costly (Ayanian, 2015). Projections of the economic boon to our society should we reduce health outcome disparities are startingly large. Finally, we have incontrovertible evidence of injustice in many of our academic reward practices, such as NIH grant receipt that unfairly privilege certain groups over others, independent of merit (Ginther et al., 2011). Thus, it is for reasons of scientific need, clinical practice improvement, economic benefit, and justice that our scientific workforce should be diverse, and demographically representative.

We chose to examine demographic representation within behavioral medicine from a number of vantage points. We wanted to know if behavioral medicine leaders, operationalized at those who were or are Principal Investigators of National Institutes of Health (NIH)-funded training grants in the field, were, themselves demographically representative, or if they had become increasingly representative across the decades that our field has existed. We also wanted to know if the topics of their training grants had diversified, and if so, for which topics this diversification had occurred. Next, we considered what constitutes success in the field of behavioral medicine. While the debate on metrics within this area would constitute an entirely separate publication, we settled for one for which we could find no prior evidence. First authorship of a peer-reviewed publication is the undisputed signal of clear leadership and intellectual contribution towards that publication. For emerging behavioral medicine scientists to advance academically, they must be first authors. While the politics, and transparency, of the agreement as to who should be the first author are complex and nuanced, the need for scholars from diverse backgrounds in our field to be first authors is not. These emerging scientists must have first-authored publications to advance. Thus, we quantified, and visualized, how our field's NIH-trained first authors have diversified to be demographically representative across the past five decades. We also chose to explore the topics of these peer-reviewed articles, to determine if topic representation, and diversity, has occurred in our field as our scientific workforce has diversified. Finally, we believe in the idiom, "one picture is worth a thousand words". We chose to illustrate our findings, so that our representation successes, and opportunities, are seen viscerally, rather than debated endlessly.

Methods

Study design and protection of human subjects

This was an observational study of publicly available publication and title records derived from NIH institutional research training grant (T32) awards in behavioral medicine, which met exempt criteria for human subjects research protection.

Data source

We used Research Portfolio Online Reporting Tools (RePORT) to identify NIH institutional research training grant (T32) mechanisms in behavioral medicine. We then extracted all training grant titles, Principal Investigator names, and all attributed publications. To retrieve relevant grants and their associated publications we searched for "T32%" in the Project Number/Application ID field AND "behavior" in the text search field, % being the truncation operator in this search engine. All 275 resulting projects were exported to an Excel spreadsheet and the irrelevant grant titles which do not directly target training of behavioral science such as genetics and neuroscience training grants excluded. For each of the 71 remaining grants, all training grant titles, Principal Investigator names, and all publications were exported to Excel. This extraction includes all of the publicly available titles of the publications and associated meta data (e.g., authors, publication year, affiliation, journal name) without personally identifiable or sensitive demographic information (e.g., gender, race/ethnicity, age). The resulting analytic corpus comprised 4302 publication records derived from 71 training grants from 1980 to 2018. We then contacted the NIH Information for Management, Planning, Analysis, and Coordination (IMPAC II) database to obtain anonymized gender, ethnicity, and race trainee data from these 71 behavioral medicine training grants from 1980 to 2017.

Detecting gender and ethnicity and race

To the best of our knowledge, we used the most accurate classifying algorithm to detect gender information from first and last names of 71 directors of the training grants and 4302 first authors of publications using R package. The gender classifying program (Ye et al., 2017) was built from analysis of

57 million contact lists from a major Internet company covering 90% of the world population by linguists, anthropologists and historians covering global languages such as Hebrew, Chinese and Georgian. In most cultures, the gender is ecoded in the first name and this gender detection data mining algorithm classifies a person as "male" or "female" based on the learning from big datasets containing gender and names collected from the world. We applied the race and ethnicity detection classifier algorithm on the last names of 71 directors and 4302 first authors of the training programs using the Python package (Sood & Laohaprapanon, 2018). The accuracy of the ethnicity and race detection algorithm is documented as 0.79 (precision) and 0.81 (recall) respectively. The detailed information of 71 directors and 4302 first authors are available as an online dataset (https://docs.google.com/spreadsheets/d/1OT3a8jn_zLaq60mbcjU7PJcsdMs67q33tPDvpd8nSTU/edit?usp=sharing).

Second, demographic information of four out of a total 71 directors of training grants (N = 4, 5.63%) was adjusted after the manual verification of a Google search conducted by two individuals (SY, MO) including one scientist with expertise in demographic coding and one scholar with expertise in minority research. Exponential smoothing modeling was applied for trend analyses to detect the demographic representation. Among 4302 first authors of the publications, 877 authors were automatically classified as unknown gender (20.39%). Gender information of 781 out of those 877 with unknown gender (89.05%) was adjusted after the manual verification of a Google search. Next, the descriptive statistics of topics and demographic information were visualized with stream diagram to elucidate time changes.

A diversity lexicon

We built a lexicon representing diversity concepts to index each record of 4302 publications. The search terms from an ongoing systematic review were used to generate an initial list, utilizing both the subject headings of databases and the textwords, and by checking for further synonyms in the subject heading definitions. We supplemented this list by searching online thesauri for additional terms. Our diversity lexicon contains three categories: (1) sexuality and gender including four subconcepts (i.e., women, transgender, gender, LGBT/gay/lesbian/bisexual/homosexual), (2) race and ethnicity including 5 subconcepts (i.e., Asian, African American/Black, Hispanic/Latino, race, ethnicity), (3) age, socioeconomic status and others including 11 subconcepts (i.e., low literacy, low income, age, elderly, children, aging, socioeconomic, bias, disability, religioin, culture/multiculture). The titles of each publication record were indexed according to the subconcepts in our diversity lexicon.

Data science and statistical analyses

Detecting topics of publications

Natural language processing assists humans to conveniently summarize a large collection of textual data through detection of hidden meaningful themes. To extract topics from the titles of the 4302 publications from training grants in behavioral medicine, we applied a generative statistical model, latent dirichlet allocation (LDA) algorithm using R (Blei, 2012). We calculated metrics (Arun et al., 2010; Cao et al., 2009; Deveaud et al., 2014; Griffiths & Steyvers, 2004) to determine the optimum number of topics.

Results

Our search revealed 71 NIH-funded T32 grants that provided training in the field of behavioral medicine. A word cloud on Fig. 1 shows topics of all National Institutes of Medicine T32 training awards on behavioral medicine for the last 43 years where a word size reflects response frequency. As Fig. 1 reveals, a disproportionate number of these training grants focused on cardiovascular behavioral medicine. 'Drug', 'Prevention', 'Abuse', and 'Biomedical', were also topic phrases/words used frequently across the decades of training.

Next, we examined the demographic representation of the training Principal Investigators (Fig. 2). Overall, there

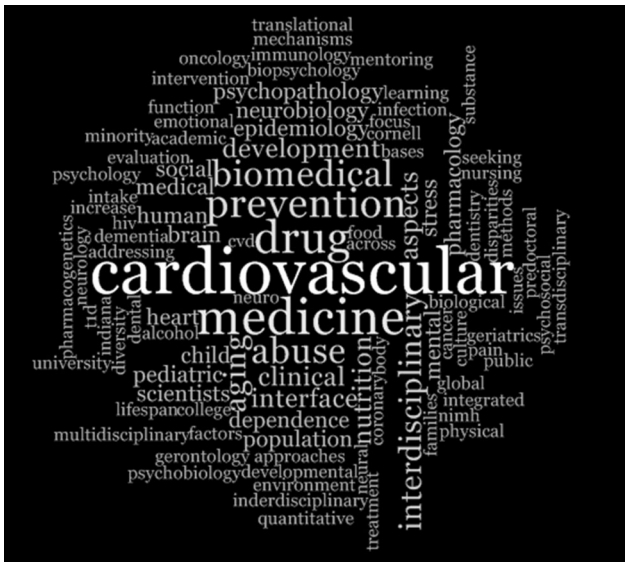

Fig. 1 Topics of All Behavioral Medicine National Institutes of Medicine T32 Training Awards from 1975 to 2018. Note: The word cloud summarizes topics of all T32 traning grants. Size of a word reflects response frequency of the word/phrases. 'Cardiovascular' is predominantly followed by 'Drug', 'Prevention, Abuse', 'Interdisciplinary' and 'Aging'

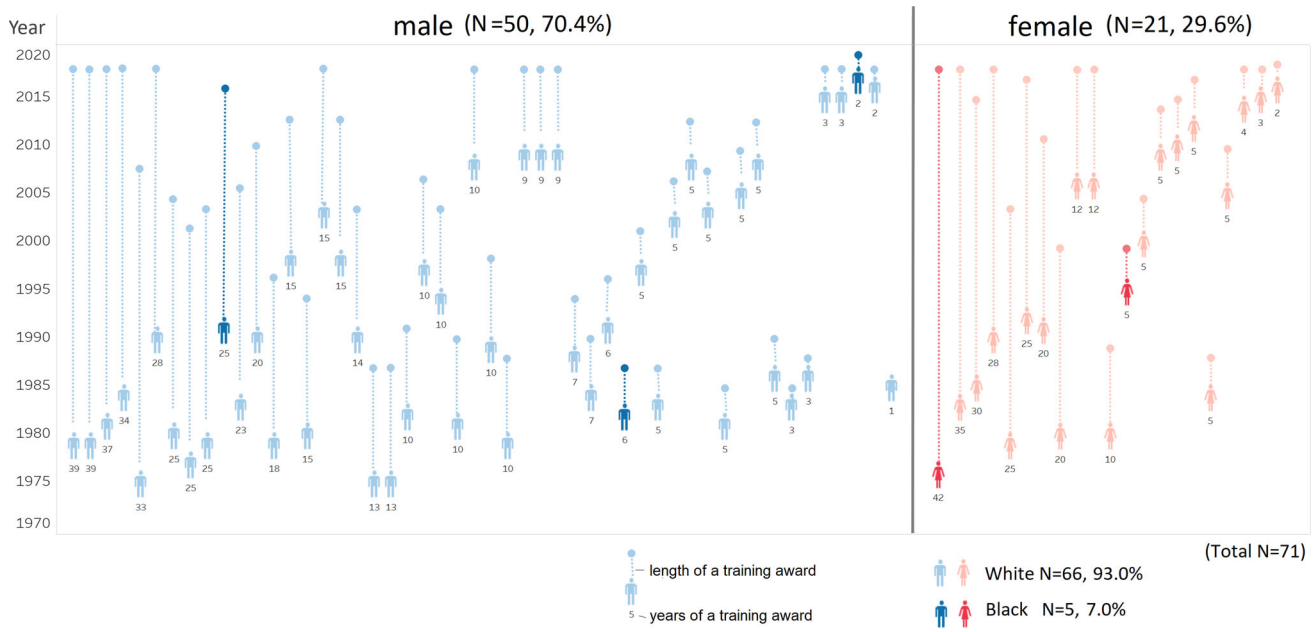

Fig. 2 Demographic representation of the Behavioral Medicine's National Institutes of Health T32 Training Directors from 1975 to 2018. Note: A human icon represents each director of a different T32 training award (shape by sex, color by race). Vertical position of a human icon and a circle (Y-axis) indicate a start-year and an end-year of an award. A dotted line represents a length of each award. For example, a black female director, who is a pioneer of behavioral medicine, has led behavioral medicine over 40 years. Five white males and one white female have lead behavioral medicine over 30 years

were 70% male, and 30% female leaders, with only 7% of the leaders being identified as African American. We could not reliably assess Hispanic ethnicity, and so this is not reported. No trend for changes in black female representation were detected. Increasing trends for black male and white female leadership were detected ($P < 0.001$) while a decreasing trend for white male leadership was also observed ($P < 0.0001$).

Behavioral Medicine trainees for the last 37 years included 4922 trainees but only included a small portion who self-identified as Hispanic (n = 235, 4.8%) or as Black or African American (n = 340, 6.9%) or as Asian (n = 326, 6.6%). As reporting changed over the decades, accurate records of the number of self-identified female trainees could not be reliably reported. The proportion of trainees who self-identified as Hispanic increased in recent years (year 1980 to 1989: n ≤ 11, 1.05%, year 1990 to 1999: n = 44, 3.23%, year 2000 to 2009: n = 92, 5.85%, year 2010 to 2017: n = 99, 9.52%). Similarly, representation from those identifying as Black or African American also increased over time (year 1980 to 1989: n = 20, 2.11%, year 1990 to 1999: n = 89, 6.53%, year 2000 to 2009: n = 130, 8.27%, year 2010 to 2017: n = 101, 9.71%) as occurred for those self-identifying as Asian (year 1980 to 1989: n = 20, 2.11%, year 1990 to 1999: n = 74, 5.43%, year 2000 to 2009: n = 141, 8.97%, 2010 to 2017: n = 91, 8.75%). According to the aggregated data provided by a Freedom of Information Act request, male counts were substantially missing from multiple years, thus we cannot reliably report on the self-identified male and female trainee representation, either in total or by decade.

Figure 3 examines the likely demographic representation of first authors from the 4302 training publications. Of these, 2806 or 65.2% were from first authors classified as likely male, and 1400 or 32.5% as likely female first authors. Of note, 2432 had white male first authors, while 101 had Asian or Pacific Islander female first authors, and 8 had Black/African American female first authors. As can be seen, since 2010 there have been small improvements in the inclusion of those first authors identified by our algorithm as Hispanic (n = 201, 4.7%), Black or African American (n = 64, 1.5%) or Asian (298, 6.9%). This represents a small proportion of all first authored publications (n = 563, 13.1%). There were 96, or 2.2% that were classified as white, but ethnicity and gender could not be accurately classified.

Finally, Figs. 4, 5 and 6 examine the topics of these 4302 publications. As can be seen, focus on race or ethnicity has been minor (n = 342, 8% across all years), as is true for publications focused on gender and/or sexual preferences (n = 439, 10% for all years). Later years of publication dates had better representation, suggesting an increasing interest in these areas of scientific inquiry.

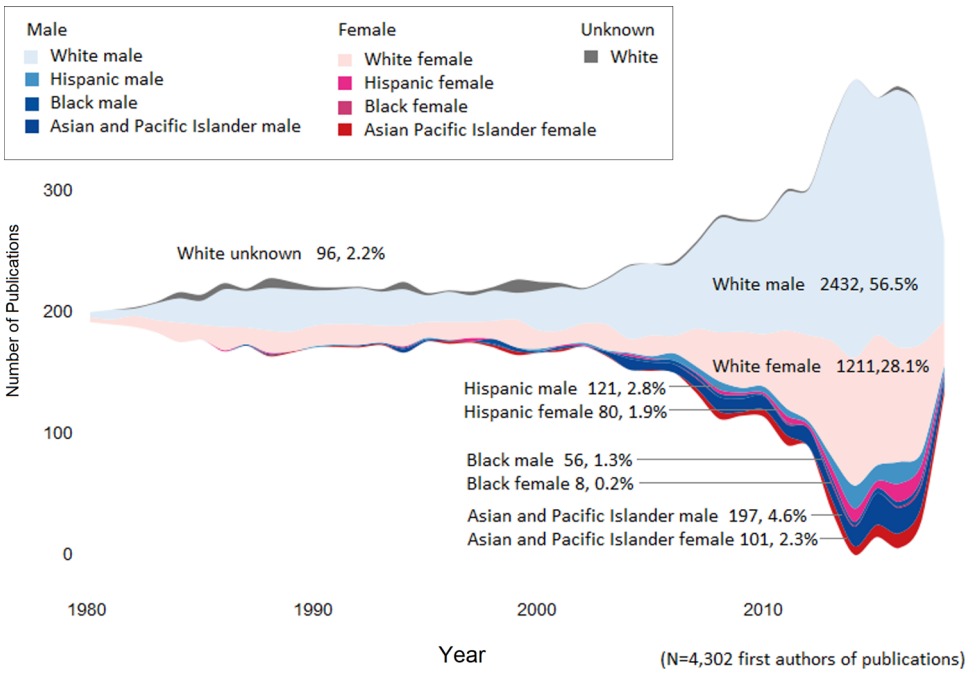

Fig. 3 Predicted Sex, Race, and Ethnicity of First Authors of the 4302 Trainee Publications attributed to National Institute of Health T32 Grants. Note: The stream graph displays chronological volume changes of predicted demographic information of first authors (N = 4302) from T32 grants. Overall, the stream volume is predominantly comprised of white male (56.2%) over the past four decades. As large volume of the first authors (over 400 authors per year) has flowed into the stream of the first authors during the past decade, increased volume of minority first authors has drascally entered into the stream of the first authors of T32 grants

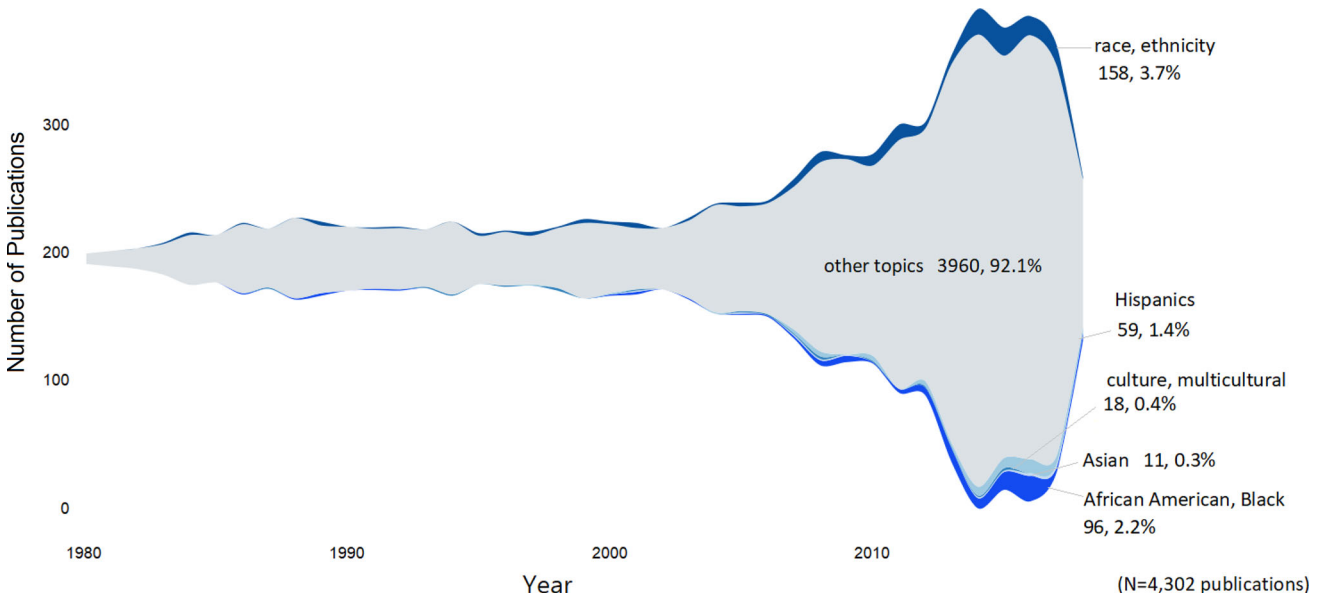

Fig. 4 Proportion of 4302 Trainee Publications attributed to National Institute of Health T32 Grants that focus on Race and Ethnicity. Note: The stream graph displays chronological volume changes of topics on race and ethnicity among 4302 publications attributed to T32 grants. Total 7.9% of 4302 publications reports topics on race and ethnicity. The subtopics consist of race/ethnicity (3.7%), African American/Black (2.2%), Hispanics (1.4%), culture/multicultural (0.4%) and Asian (0.3%). The volume of topics on African American/Black and race/ethnicity has rapidly increased over the past 5 years

Discussion

Our 'look' at demographic and topic representation in the field of behavioral medicine has revealed several interesting insights. First, women have been represented as training leaders in our field since the beginning of our discipline. However, increasing ethnic representation has not occurred, particularly for African American female training leaders. We have supported a robust number of trainees across the last four decades, with almost 5000 trainees having received T32 support from NIH over almost four decades. However, neither our leaders nor our trainees are representative of the current United States demographics. The 2014 prevalence estimates for the

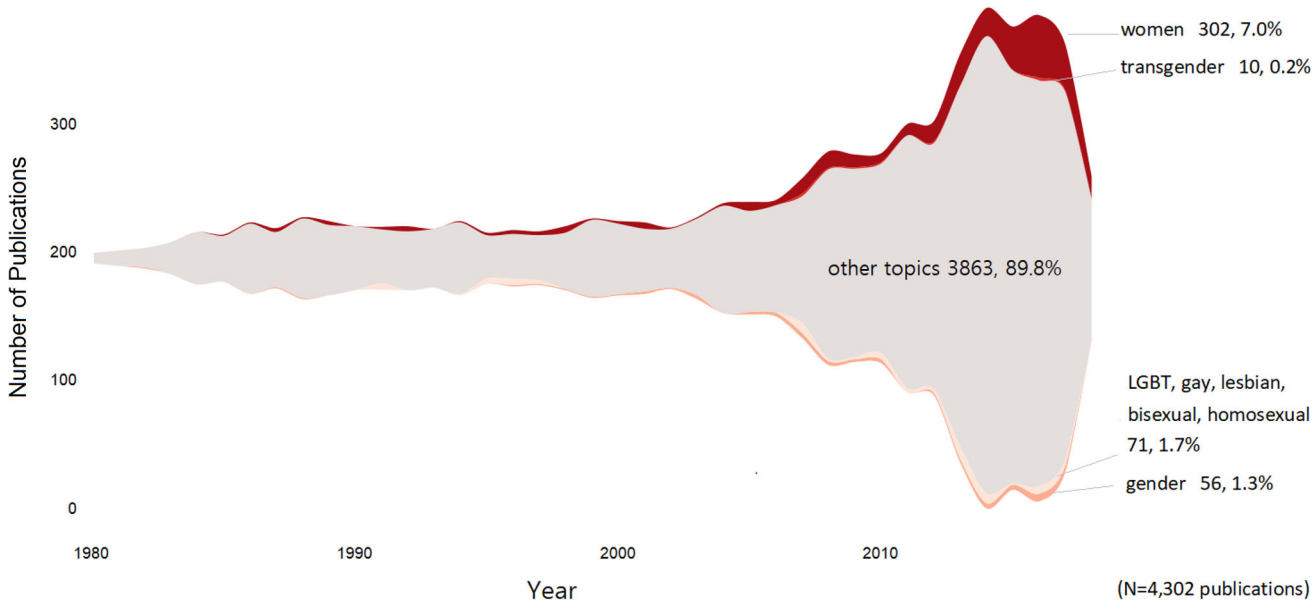

Fig. 5 Proportion of 4302 Trainee Publications attributed to National Institute of Health T32 Grants that focus on Gender. Note: The stream graph displays chronological volume changes on gender topics among 4302 publications attributed to T32 grants. Total 10.2% of 4302 publications contributes topics on gender. The subtopics consist of women (7%), LGBT/gay/lesbian/bisexual/homosexual (1.7%), gender (1.3%) and transgender (0.2%). The volume of topics on women and LGBT/gay/lesbian/bisexual/homosexual has abrubtly increased over the past decade

United States population are 51% female, 17.4% Hispanic, 13% Black or African American, and 5% Asian individuals (Colby & Ortman, 2015). Even in 2017, our training leaders who were heuristically verified are currently only 29.6% female and 7% Black or African American; we were unable to reliably detect Hispanic identities and so this is unknown. For our trainees, even in the last few years, we under-represent the demographics of the United States. The decades of 2000–2009 and 2010–2017 revealed approximately 6 and 10% of trainees self-identified as Hispanic and this is contrasted with 17.4% Hispanic 2014 U.S. population estimates. Similarly, 2000–2009 and 2010–2017 revealed approximately 8 and 10% of trainees self-identified as Black/African American, but U.S. population estimates are that 13% self-identify as Black or African American. Our later decades of training have 9.0% and 8.7% self-identified Asian representation, and this percentage compares favorably to the U.S. population estimates of 5.0%. Clearly, examining our trends across the decades, we have improved trainee representation; there is more to be done, but there is encouraging news in our trainee identification and selection process in behavioral medicine.

However, juxtaposing trainee and first author demographic representation reveals a troubling issue. Trainees self-identifying as Hispanic (4.8%) and first authors identified as likely Hispanic (4.8%) were approximately equivalent. However, trainees self-identifying as Black or African American (6.9%) were drastically under-represented as first authors (1.5%). This is exemplified by first authors identified as likely African American and female; publications for this demographic group was only 8 in 37 years, or 0.2% of the body of all attributed training publications.

Our training grant topics have clearly diversified over the decades, as have the topics of the training publications. A focus of these publications on race and/or ethnicity has begun to emerge in the last 10 years, as has increasing focus on topics such as multi-culturalism and culture. Similarly, the last 10 years have seen a drastic increase in publications focusing on women, and a smaller increase in publications focusing on sexual orientation. Children have been the focus of publications for several decades, but focus on the social determinants of health—low literacy, low income, bias, and socioeconomic status has only occurred in the last few years. While we did not conduct formal associational tests of the changing workforce and the changing topics, given the disparities of our data sets, the co-occurrence of this diversification is worth noting. Reducing our nation's health disparities and advising health policy about how to do so requires studying these diverse topics (Smedley et al., 2004) and at the qualitative, observational level, it appears we fulfill our mission of studying more diverse topics as our trainee workforce diversifies.

Our observational analysis is not without limitations. We employed the most accurate identification algorithms to determine gender, race, and ethnicity, for the training

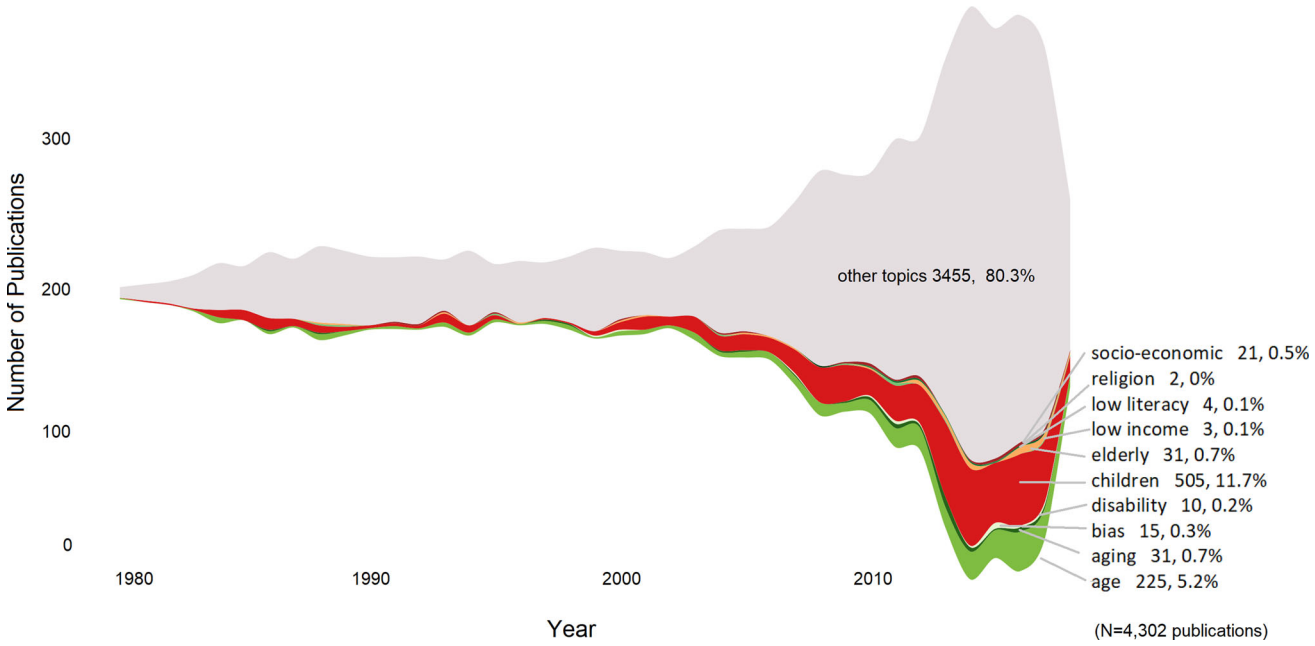

Fig. 6 Proportion of 4302 Trainee Publications attributed to National Institute of Health T32 Grants that focus on of Social Determinants of Health. Note: The stream graph displays chronological volume changes of topics on social determinants of health among 4302 publications attributed to T32 grants. Total 19.7% of 4302 publications reports topics on social determinants of health. The subtopics consist of children (11.7%), age (5.2%), aging (0.7%), elderly (0.7%), socio-economic (0.5%), bias (0.3%), low literacy (0.1%) and disability (0.2%). The volume of topics on children and age has rapidly increased over the past decade

leaders and for the first authors of the training publications. However, these are not completely accurate, leading to the possibility of mis-identification. As noted above, we could not reliably detect Hispanic ethnicity training leaders, and so we were unable to report this statistics. As our request for the self-identification demographics of trainees was anonymized and grouped, we are not able to match trainees individually to their first authored publications. Further, the grouped, anonymized report of the ethnicity and race of trainees that had cells containing 11 or less were suppressed, again leading to the possibility of inaccuracy in some of our estimates. In addition, we could not report accurately on the proportion of trainees self-identifying as female, because training report standards changed over the decades. Nevertheless, this was a first step at attempting to quantify and examine trends in a large workforce, using the empirically best-supported algorithms. Finally, although our use of the NIH T32 mechanism provided useful data for the exploration of demographic trends in behavioral medicine, especially given the impact of these training grants on the field, it is possible that other grant mechanisms (e.g., the R01 or K mechanisms) might have revealed somewhat different findings. However, recent analyses of overall NIH funding show a similar pattern of findings with regard to the underrepresentation of diverse ethnic and racial groups among principal investigators (Ginther et al., 2011). Recent findings from across NIH also indicate a greater diversification of research topics with respect to race, ethnicity, and gender within medicine as well, but also indicate that more progress is desperately needed (Oh et al., 2015).

Conclusions and future directions

Representative behavioral medicine researchers from diverse backgrounds matter for science, for patients, and ultimately for public health. What can we do to eliminate the representation gaps in our research workforce and in our first author publications?

As scientists, we know that data and quantitative analyses frequently reveal, while words and debates can obfuscate. Creating a clear, transparent method by which we can all appreciate the progress that we have, or have not, made in increasing the demographic representation in our scientific workforce is an important first step. We need a dashboard or scorecard that regularly updates the statistics we report here, and that details quantitatively the diversity trends that occur among our leaders, our trainees, and our products. Stewardship of this initiative is not clear, but without numbers, and pictures, it is easy for hidden biases, impressions, and heuristics to convince us we are progressing, when perhaps we are not.

Fixing the first author problem

Improving the representation of our first authors from our training efforts will be key to assuring the success of these future scientists. First authorships for peer-reviewed publications signal many things; intellectual contribution, scientific leadership, future grants-personship potential, or promise for successful tenure and promotion. First authorship is decided based on a number of explicit, and implicit factors; it is the culmination of a complex interplay of career development, of mentorship, of funding, and of support (Rexrode, 2016). Inequity in first author representation must therefore be tackled at the level of journals, editors, reviewers, mentors, and future authors by helping all these parties to develop and implement journal and review policies that promote fairness, transparency, and equity (Rexrode, 2016). We also can help by starting to tackle the personal biases that filter through all the complex processes involved in the pathways to academic success, including the decision about who is first author. For example, even in a 2017 publication on the contributions made by senior, other, and first authors, the resulting factors from their factor analysis were described as 'thinker', 'soldier', 'scribe' (Perneger et al., 2017). Now ask yourself this: did an Hispanic or African woman first cross your mind when you read 'soldier'?

In a review of other barriers for behavioral medicine scientists from diverse backgrounds, a study was conducted with successful behavioral medicine scientists from around the country, in different areas, and from diverse backgrounds. The top barriers identified are shown in the Table 1.

Table 1 Barriers Identified by Minority Behavioral Medicine Scientists (Kameny et al., 2013)

Institutional
Lack of writing time
Lack of mentor
Departmental politics
Culture
Racism (general)
Research on minority populations not valued
Low expectations
Skills
Time management
Research skills
Grant writing

Representation is not enough

Only monitoring the representation of our scientific workforce will not attain the ambitions we have for our field to provide useful and effective answers to the fundamental questions central to disease prevention and health promotion efforts (National Research Council, 2011). We have many examples where even appropriate representation in a scientific workforce is not sufficient to ensure academic success. For example, when men and women reviewers rated identical scientific resumes randomized to (fictional) male or female sounding names, both types of reviewers rated the job applicant or the possibility of tenure as less likely when the candidate was purportedly female (Foschi et al., 1994; Steinpreis et al., 1999). There was a recent investigation of outcomes for men (N = 573) and women scientists (n = 493) receiving prestigious NIH K08 or K23 awards (Jagsi et al., 2017). By 5–8 years after the initial award receipt, women had significantly less funding (average of $780,000 vs. $1,120,000) and also had fewer publications (average of 33 vs. 45). The authors compiled a composite measure of success comprised of funding, publications, and/or leadership positions, and 53% of women and 67% of men were academically successful by this measure. The authors then recalculated this success metric after accounting for: K award type (K08 vs. K23), specialty, award year, work hours, funding institute tier, feeling responsible for participating in department/division administration, importance of publishing prolifically, feeling responsible for contributing to clinical care, importance of publishing high-quality research, collegiality of the mentoring relationship, adequacy of research equipment, and departmental climate. The stark gender difference in academic success remained (Jagsi et al., 2017). Thus, representation without inclusive environments and without equity efforts often simply lead to further injustice. There are now a number of empirical interventions to address these issues, briefly outlined here.

There have been a number of interventions to improve and provide more effective mentoring to scientists from diverse backgrounds. Formal training was provided to mentors (n = 34) across the U.S, including understanding the impact unconscious bias, microaggressions, discrimination, and tokenism for mentees, and providing specific tools and techniques for effective mentoring. Pre- and post-training evaluations revealed significant improvements as assessed by a validated mentoring competency tool (Johnson & Gandhi, 2015). A randomized controlled trial involving 283 mentor–mentee pairs from several academic health centers demonstrated that formal, competen-cy-based research mentor training improved mentoring behavior (Pfund et al., 2014). Training was provided in six key competencies: (1) maintaining effective communica-

tion, (2) establishing and aligning expectations, (3) assessing mentees' understanding of scientific research, (4) addressing diversity within mentoring relationships, (5) fostering mentees' independence, and (6) promoting mentees' professional career development. Importantly, intervention mentees reported more changes in their mentors' behavior than did control mentees.

On the national front, a number of empirical investigations are now underway. Drastic disparities in NIH R01 funding for Afri-can-American scientists were recently reported (Ginther et al., 2011). In response to these findings and to an advisory report, NIH has recently launched an experimental program to evaluate evidence-based practices in recruitment and retention of underrepresented students. They are also creating infrastructure to develop faculty from divserse and representative backgrounds. The $250 million, 5-year Diversity Program Consortium to accomplish these aims (www.diversityprogramconsortium.org) consists of three programs: the Building Infrastructure Leading to Diversity (BUILD) program; the National Research Mentoring Network (NRMN); and a Coordination and Evaluation Center. This experimental set of awards is providing data to help shape and inform current and future diversity training programs (Valantine et al., 2016). The European commission has recently begun a study to investigate possible sources of gender bias in academic evaluation processes, instead of assuming that quotas of women on review boards or in other positions will be sufficient to remedy the current gender imbalance in grants, professorship, and leadership (Vernos, 2013).

It is time to tackle all components of our checkpoints along the pathway to successful full professors (Meyers et al., 2018). Diversity in our science topics, our training topics, and in our research findings will flourish when diversity is welcome, whether it is in our study populations, in our academic faculty, in our NIH study sections, in our journal reviewers and editors, or in our boardrooms (Oh et al., 2015). Consider what you can do in your behavioral medicine program to diversify and support your trainees, to aid your colleagues, and to welcome and nurture our next generation of representative behavioral medicine scientists.

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Compliance with ethical standards

Conflict of interest Sunmoo Yoon, Louise Falzon, Norman B. Anderson and Karina W. Davidson report no real or apparent conflicts of interest.

Human and animal rights and Informed consent This article does not contain any studies with human participants or animals performed by any of the authors.

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