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Gender in Science, Technology, Engineering, and Mathematics: Issues, Causes, Solutions

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Abstract

The landscape of gender in education and the workforce has shifted over the past decades: women have made gains in representation, equitable pay, and recognition through awards, grants, and publications. Despite overall change, differences persist in the fields of science, technology, engineering, and mathematics (STEM). This Viewpoint article on gender disparities in STEM offers an overarching perspective by addressing what the issues are, why the issues may emerge, and how the issues may be solved. In Part One, recent data on gaps in representation, compensation, and recognition (awards, grants, publications) are reviewed, highlighting differences across subfields (e.g., computer science vs. biology) and across career trajectories (e.g., bachelor's degrees vs. senior faculty). In Part Two, evidence on leading explanations for these gaps, including explanations centered on abilities, preferences, and explicit and implicit bias, is presented. Particular attention is paid to implicit bias – mental processes that exist largely outside of conscious awareness and control in both male and female perceivers and female targets themselves. Given its prevalence and persistence, implicit bias warrants a central focus for research and application. Finally, in Part Three, the current knowledge is presented on interventions to change individuals' beliefs and behaviors, as well as organizational culture and practices. The moral issues surrounding equal access aside, understanding and addressing the complex issues surrounding gender in STEM is important because of the possible benefits to STEM and society that will be realized only when full participation of all capable and qualified individuals is guaranteed.

Keywords: gender, STEM, implicit bias, explicit bias

Prologue

For centuries, the essence of what constitutes the human "female" and "male" has been portrayed through a lens of difference, even opposition (e.g., Gray, 1992). In theological, philosophical, literary and scientific thought as well as in folk beliefs, "female" is represented as mentally lesser, weak, and relying on emotion, while "male" is represented as mentally superior, strong, and relying on rationality (Keller, 1985). As a consequence, women's lack of success, leadership, and representation in fields that emphasize rationality – especially fields of science, technology, engineering, and mathematics (STEM) – used to be seen simply as a consequence of men and women's divergent nature and capacities (Keller, 1985).

Over the past fifty years, many of these beliefs are now antiquated (General Social Survey, 2019; Saad, 2017), having been challenged by women's advances into academe and the workforce, especially in the arts and humanities, but also in STEM. Today, U.S. women earn 57% of bachelor's degrees overall and 50% of bachelor's degrees in STEM (National Science Foundation, 2018). Gender parity is now within reach in the U.S. workforce (World Bank, 2018), and there remains no STEM field without representation of women, even in high status positions (National Science Foundation, 2018). As such, the issue of "gender in STEM" is no longer about whether women have the capacity to succeed but rather the costs to STEM that will occur without the full participation of all qualified and capable candidates, including women. Regardless of one's personal feelings about uplifting women, the reality is that a diverse workforce and academe can provide both financial (e.g., Credit Suisse, 2012; Dezsö & Ross, 2012) and intellectual benefits (e.g., Galinsky et al., 2015; Loyd, Wang, Phillips, & Lount, 2013). Thus, gender diversity is necessary to meet the demands of innovation and productivity in complex STEM environments (Page, 2011, 2018).

To understand how such demands of innovation and productivity can be fulfilled, behavioral scientists study the barriers to access and opportunity, especially those arising from explicit and implicit attitudes and stereotypes held by both men and women. To this end, the current Viewpoint article evaluates recent evidence on the extent, causes, and solutions to gender disparities in STEM, with a particular focus on the role of implicit cognition – mental processes that reflect "traces of past experience… unavailable to self-report or introspection" and are therefore less conscious and controllable than their explicit counterparts measured through self-report (p. 4, Greenwald & Banaji, 1995).

In Part One, the magnitude of gender gaps in STEM representation, compensation, authorship, grant success, and awards is presented, as well as how these gaps have changed over time. In Part Two, leading hypotheses about the causes of such gender gaps are evaluated. Specifically, that women lag behind in STEM because of (1) innate and/or socially-determined gender differences in abilities necessary for success, (2) innate and/or socially-determined gender differences in preferences, lifestyle choices, or values among women and men, and (3) explicit and implicit bias in both women and men as they evaluate the work of women and men in STEM. Finally, in Part Three, interventions to reduce gender disparities in STEM by targeting both individual minds and organizational culture and practices are reviewed.

Part One: The Extent of Gender Disparities in Science

1.1 Representation

The gender gap in science, technology, engineering and mathematics (STEM) representation starts early. By middle school, more than twice as many boys than girls intend to work in science or engineering-related jobs (Legewie & DiPrete, 2012). These differences continue through high school courses, particularly in computer science, engineering, and related sub-fields

(Cunningham & Hoyer, 2015). For instance, although female U.S. high school students constitute 61% of AP biology, 52% of AP statistics, and 50% of AP chemistry students, they represent only 23% of AP computer science and 29% of AP physics students (National Science Foundation, 2018). In college, these disparities increase: 5 times more men than women report an intention to major in engineering and computer sciences (Figure 1, Radford, Fritch, Leu, Duprey, & Christopher, 2018).

Figure 1. *Gender gap in intent to major in STEM and non-STEM fields among U.S. college entrants.* Data retrieved from National Center for Education Statistics High School Longitudinal Study, table 10 (Radford et al., 2018). See https://osf.io/n9jca/ for raw data and code.

While previous research stressed the issue of a "leaky pipeline" between college and graduate school (with women being particularly likely to opt out, or be pushed out, at this educational transition) new data suggests that, in the U.S., the college-to-graduate school transition no longer leaks more women than men (Miller & Wai, 2015). As such, attention must be redirected to earlier transitions including middle school-to-high school (Legewie & DiPrete, 2012), and high school-to-college (Shaw & Stanton, 2012), which are important both because they serve as gatekeepers for later STEM transitions, and also because "leaks" are still apparent at these junctions.

Even after persisting through early STEM education, women remain underrepresented throughout higher education in the U.S., again particularly in computer science and engineering (Table 1, Figure 2). While women now account for 57% of bachelor's degrees across fields and 50% of bachelor's degrees in science and engineering broadly (including social and behavioral sciences), they account for only 38% of bachelor's degrees in traditional STEM fields (i.e., engineering, mathematics, computer science, and physical sciences, Table 1). Moreover, over the past 15 years, the percentage of female associate's or bachelor's degree holders has remained stagnant in many STEM subfields (Figure 2).

Strikingly, the representation of women has even decreased in computer science, with female associate's degrees dropping from 42% in 2000 to 21% in 2015, and the percent of female bachelor's degrees dropping from 28% in 2000 to 18% in 2015 (National Science Foundation, 2018). Although explanations are elaborated in Part Two, the unique decreasing representation of women in computer science warrants consideration here. It is possible that increasing participation in pre-college computer science training (The College Board, 2018), coupled with the lack of early female role models or teachers in computer science, may increasingly lead young girls to pre-emptively opt out of college computer science because they have already internalized the stereotype that they do not belong (e.g., Master, Cheryan, & Meltzoff, 2016). Explaining the case of computer science representation remains a necessary direction for future research.

Finally, it is worth noting that underrepresentation in doctorate-level STEM education is greatest at the top 10% of institutions (Weeden, Thébaud, & Gelbgiser, 2017). This suggests that factors including self-selection and/or status-based biases may continue to limit women's success throughout higher education (see Part Two).

Figure 2. Proportion of degree earners that are females across post-secondary education (2000 – 2015) overall and in STEM subfields. Proportions of students in each field and degree that identify as female in (a) all science and engineering (S&E) fields including social and behavioral science (SBS), (b) traditional S&E fields (excluding social and behavioral sciences), (c) all non-S&E fields, as well as STEM subfields of (d) Computer Science, (e) Mathematics, (f) Engineering, (g) Physics, and (h) Biology. Data retrieved from National Science Foundation (2018). See https://osf.io/n9jca/ for compiled raw data and code.

As women progress into the academic and non-academic workforce, they continue to be represented in lower numbers than men. In traditional STEM fields, despite earning 34% and 41% of MAs and PhDs, respectively, women compose only 25% of the STEM workforce and 27% of full-time, tenured professors (Table 2, Corbett & Hill, 2015; Hill, Corbett, & St Rose, 2010; National Science Foundation, 2018). Additionally, although gains have been made in faculty representation since the 1970s, the increases for senior faculty are often slower than increases for junior faculty and postdoctorates (National Science Foundation, 2018). In the case of computer science, for example, the percentage of female senior faculty has been relatively slow over the past 15 years, decreasing only 5 percentage points from 24% in 1999 to 19% in 2015, slower than the change in the percentage of junior faculty (which increased by 8 percentage points).

Importantly, this apparent stagnation in senior positions is partly a consequence of "demographic inertia," or that women's later entrance in STEM results in more junior than senior faculty (e.g., Hargens & Long, 2002). However, computer simulations of women's career progress shows that gender gaps in higher status STEM positions are not entirely explained by inertia and the later entrance of women in STEM (Shaw & Stanton, 2012). These simulations show that, if the lack of female senior faculty were attributable entirely to inertia, women would have made faster progress than what is observed in the real data. As such, additional factors, such as that the greatest demands of childbearing on women often coincide with the timing of tenure decisions (Cech & Blair-Loy, 2019), also appear to contribute to the low numbers of female senior faculty. This conclusion is crucial because it suggests that we cannot assume time alone will solve the issue of gender disparities in STEM.

Taken together, the data on representation provide three conclusions. First, gender gaps in STEM course-taking and interest emerge as early as middle and high school, with these early transitions crucial in gatekeeping later participation in STEM. Second, gender gaps are most pronounced, and have even increased over time, for subfields of computer sciences and engineering. Gaps in these two subfields have a disproportionate impact on the participation and advancement of women in STEM because they represent over 80% of the STEM workforce (Landivar, 2013) and offer the highest monetary return on educational investment (Corbett & Hill, 2015). Third, the gender gap in the academic workforce is greatest in tenured and high-status faculty positions, and these gaps cannot be solved by time alone. Differences in representation provide the most basic data for the issue under review: they show a consistent lack of women in STEM careers and, because women are as capable as men to succeed in STEM (see Part Two), the result is a loss of productivity and innovation to both STEM and society (Page, 2018).

1.2 Compensation

Even when female scientists enter and persist in STEM careers, their economic compensation is not equal to that of their male colleagues (American Association of University Women, 2018; Blau & Kahn, 2017; National Science Foundation, 2018). In raw dollars, women in the U.S. STEM workforce are paid $20,000 less than men, receiving the equivalent of 79% of men's earnings (Table 3).

When such statistics are reported, however, they are often mistakenly assumed to mean that women make 79% of men's earning, for the same work. This is not the case. The 79% statistic is confounded by additional gender differences in: (1) representation of subfields, with men overrepresented in private for-profit sectors versus non-profit sectors, as well as in high-paying computer science/engineering versus lower-paying biology (see section 1.1 above); (2) seniority, with women's later entrance in STEM leading women scientists to be younger on average , thus leading to lower compensation as a function of age and experience (National Science Foundation, 2018); and, finally, (3) the status of jobs held by men and women, with women more likely to occupy low-paying part-time positions, often to fulfill caregiving responsibilities (Cech & Blair-Loy, 2019).

Nevertheless, even after controlling for correlated variables to compare men and women doing equal work at equal ages and experience levels, women in STEM are still found to receive 9% less than men (National Science Foundation, 2018). Similarly, controlling for confounding variables does little to change the gender pay gap in male-dominated subfields (e.g., computer science and engineering; Michelmore & Sassler, 2017). This persistent difference is especially notable when compounded over a career. For example, recent simulations of gender pay gaps in medical sciences suggest that a pay gap of just 3% can accumulate into a difference of over $500,000 in additional accumulated wealth across a scientist's career (Rao et al., 2018).

Importantly, as with all the data presented in this paper, the gender pay gap does not affect all women and men equally. Intersections with marital and parental status reveal a "motherhood penalty" for women with children and a "fatherhood bonus" for men with children (Benard, Paik, & Correl, 2008; Correll, Benard, & Paik, 2007). For instance, with each child, mothers' wages are reduced by approximately 5%, even after controlling for other factors such as work hours and experience. Indeed, experimental audit studies indicate that, for identical applicants differing only in parental status, mothers were offered approximately $11,000 less than women without children (a gap of 7%) , and approximately $13,000 less than fathers (a gap of 9%, Correll et al., 2007). These same studies also indicate that a father is compensated approximately 4% more than an identical male candidate without children. These pay gaps are, in turn, explained by the perception that parenthood builds men's, but reduces women's, commitment (Correll et al., 2007), as well as the perception that mothers must trade between warmth and competence, while fathers are perceived as both warm and competent (Cuddy, Fiske, & Glick, 2004).

Intersections between gender and race are also noteworthy for pay gaps: for instance, Latina women in STEM earn only 54% of White men's earnings (American Association of University Women, 2018). Although intersectional data remains unfortunately rare, such findings reinforce that future research must collect fine-grained demographic data to better understand how outcomes (including compensation, representation, and recognition) operate across multiple identities.

1.3 Grant Success, Authorship, and Awards

Grant success. Unlike the data on gender differences in representation and compensation, gender gaps in overall grant success rates now appear small to non-existent. While early studies of funding patterns suggested that women were less likely to receive grants than men (e.g., in Sweden, Wenneras & Wold, 1997), this no longer appears to be the case among many U.S. funding agencies. Across the National Science Foundation (NSF), United States Department of Agriculture (USDA), and the National Institutes of Health (NIH), the percentage of female applicants receiving grants is now approximately equivalent to the percentage of male applicants receiving grants (Hosek et al., 2005; Pohlhaus, Jiang, Wagner, Schaffer, & Pinn, 2011; U.S. Government Accountability Office, 2015). This progress towards granting parity is likely the result of the conscious efforts of governmental funding agencies to collect the necessary data and conduct formal reviews of their own evaluation processes and possible biases (e.g., through the NSF Authorization Act of 2002; Hosek et al., 2005). In addition to such observational data showing similar success rates for men and women, recent experimental studies also indicate similar granting rates for identical male and female grant applicants (Forscher, Cox, Brauer, & Devine, 2019).

Nevertheless, subtle disparities linger. First, women are less likely to reapply (i.e., renew) their grants at NSF and NIH, with a 20% difference in renewal/reapplication rates at NIH and a 5% difference in renewal/reapplication rates at NSF (Hosek et al., 2005; see also Pohlhaus et al., 2011). Gender differences in the likelihood to renew a grant imply possible gender differences in research persistence (Hechtman et al., 2018), and may therefore be related to the aforementioned loss of female faculty at the junior-to-senior faculty transition.

Second, crucial data are lacking from funding bodies that represent particularly male-dominated subfields with an engineering or defense focus (e.g., NASA, Department of Defence, DARPA, Department of Energy), where larger gender gaps in grant success rates may emerge (U.S. Government Accountability Office, 2015). As long as such agencies fail to collect or report the necessary data, beliefs such as "DARPA does not fund women" will continue to circulate in the academic folklore. Such beliefs may dissuade applications and, as a consequence, reduce the likelihood of receiving top quality applications from both female and male candidates.

Third, women appear less likely to apply for the top 1% of large grants at NIH (Hosek et al., 2005). This difference in applying for the largest NIH grants may contribute to the observation that NIH grants held by women are, on average, smaller in dollar amounts than the grants held by men (Hosek et al., 2005; Oliveira, Ma, Woodruff, & Uzzi, 2019; Waisbren et al., 2008). However, observing overall differences in dollar amounts need not entail bias on behalf of the granting agency. Lower overall amounts may be due to either (1) women requesting less than men and therefore receiving less (suggesting no bias), or (2) women and men requesting similar amounts but women receiving less (suggesting bias). NSF reports data on both the amount requested and received and finds no gender differences in either the amount requested or received, suggesting no bias. However, the NIH only reports data on the amount received, making it impossible to determine the existence (or absence) of bias because the amount received cannot be directly compared with the amount actually requested. Collection and reporting of both requested and received amounts across applicant genders is foundational to identifying and understanding possible gender bias in STEM grants.

Finally, recent studies of Canadian Institutes of Health Research revealed that grant reviewers told to focus on evaluating the "scientist" (rather than the "quality of the science") were 4 percentage points more likely to fund grants from men over women (Witteman, Hendricks, Straus, & Tannenbaum, 2019; see also Tamblyn, Girard, Qian, & Hanley, 2018). This reinforces that evidence of lingering gender gaps in grant success rates are unlikely to be due to differences in the quality of women's and men's actual proposed research. but rather to the reviewer's biased beliefs about women and men as researchers.

Despite these subtle differences in how male and female scientists consider, and are considered by, granting agencies, the general trends of parity in grant success are notable when contrasted with the disparities in compensation discussed above. As such, identifying the factors that explain grant parity, including the possible role of transparency in federal agencies (versus privacy in salary information), will inform theories about the causes and solutions to gender disparities in STEM more broadly.

Authorship. Like grant success, gender gaps in authorship of scientific publications are subtle. Aggregate statistics suggest that many fields and journals have attained gender parity in the success rates of female and male authors (Allagnat et al., 2017; Brooks & Della Sala, 2009), and the majority of fields are on their way towards parity (Holman, Stuart-Fox, & Hauser, 2018). Nevertheless, some journals continue to favor manuscript submissions from authors of their own gender (Murray et al., 2019), and many fields, including computer science, physics, and math, suggest a gender gap in authorship that will persist for decades (Holman et al., 2018).

Furthermore, gaps are most notable for last authorships (now regarded in many fields as the highest-status authorship position), where women are often represented at lower rates than would be expected given their representation in senior faculty positions (Table 4 vs. Table 2, Holman, Stuart-Fox, & Hauser, 2018; Shen, Webster, Shoda, & Fine, 2018; West, Jacquet, King, Correll, & Bergstrom, 2013). Additionally, although both male and female researchers have increased in publication rates over the past decade, some fields (e.g., psychology) have seen relatively greater increases among men, leading to an increasing gender gap in authorship over time (Ceci, Ginther, Kahn, & Williams, 2014; Holman et al., 2018). Finally, in contrast to parity in authorship across most other fields, the data from neuroscience continue to show that women publish significantly fewer first and last author papers than men (Schrouff et al., 2019; see also biaswatchneuro.com).

Awards. Finally, awards for research in STEM remain male-dominated. Across 13 major STEM society awards, 17% of award winners were female (Lincoln, Pincus, Koster, & Leboy, 2012) compared to the base-rates of representing 38% of STEM junior faculty and 27% of STEM senior faculty (Table 2). Underrepresentation is especially notable in prestigious awards: women represent 14% of recipients for the National Medal of Science, 12% for the Nobel Prize in Medicine, 6% for the American Chemical Society Priestly Medal, 3% for the Nobel Prize in Chemistry, 3% for the Fields Medal in mathematics, and 1% for the Nobel Prize in Physics (RAISE project, 2018).

While it could be that such underrepresentation is due, in part, to the relatively later entry of women into STEM (i.e., aforementioned "demographic inertia" Hargens & Long, 2002), such an explanation would not be applicable to early-career awards. In line with the notion of intertia accounting for award gaps, some early-career awards, such as the Presidential Early Career Award for Scientists and Engineers (PECASE) (38% women recipients among NSF nominees) and the Society for Neuroeconomics Early Career Award (40% women recipients) reveal award rates similar to the base rate of 38% of Junior Faculty. Nevertheless, other early-career awards continue to show disparities including the Society for Neuroscience Young Investigator Award (19% women recipients), and the Elsevier/VSS Young Investigator Award (25% women recipients). Moreover, one of the most prestigious early-career awards – the NSF Alan T. Waterman Award – has been won by only 6 women over the past 43 years (14% of recipients). These early-career data emphasize that, although some progress has been made, solving gender disparities in STEM awards is again not simply about waiting for women to "catch up" (Shaw & Stanton, 2012).

Underrepresentation in research awards contrasts with overrepresentation in teaching and service awards (Metcalfe, 2015). For example, in astronomy, where the base-rate is that women receive 10% percent of PhDs, women receive 3% of scholarly awards but 15% of teaching and service awards (Popejoy & Leboy, 2018). As discussed in Part Two below, the reasons for such overrepresentation in teaching awards are likely complex, including women's advantages in language and communication abilities, as well as differences in where women versus men are expected to succeed. Indeed, the recognition of women for teaching but not research aligns with the expectations that women are warm but incompetent (Fiske, Cuddy, Glick, & Xu, 2002; Glick & Fiske, 1996), and therefore should be good teachers but poor researchers. In sum, evidence is strong that gender disparities in STEM encompass gaps in representation, compensation, research awards and, to a lesser extent, grant success and authorship.

Part Two: Presumed Causes of Gender Disparities in Science

In the past, a dominant assumption about gender disparities in STEM concerned women's lack of ability due to biological, innate and/or immutable differences (Keller, 1985). Over time, a more complex possibility was added: observed gender differences may not be exclusively shaped by innate or immutable abilities but may also be influenced by sociocultural factors (Ceci et al., 2014). Along a different dimension, it was previously assumed that the social barriers to women's entrance and advancement in STEM were exclusively from the prejudices held by men about women. Over time, this assumption has also been revised: both men and women evaluators can be involved in gender discrimination (e.g., Moss-Racusin, Dovidio, Brescoll, Graham, & Handelsman, 2012). Finally, while the focus was previously on the biases of other people evaluating the work of women*,* a more complex thesis also looks at possible bias within both women and men themselves, including their own preferences, biology, and social experiences that may encourage opting in (or out) of certain careers (e.g., Diekman, Brown, Johnston, & Clark, 2010). Thus, the presumed causes of gender disparities in STEM have shifted over time as new evidence and interpretations emerge.

Today, the debates surrounding the causes of gender disparities in STEM often settle around three inter-related hypotheses. Gender disparities may arise from (1) innate and/or socially-determined gender differences in STEM ability, (2) innate and/or socially-determined gender differences in STEM preferences and lifestyle choices, and (3) explicit and implicit biases of both men and women in perceptions of men and women's work.

2.1 Differences in Ability

Given the complexity of STEM careers, the abilities predicting success must be diverse. Yet for most of the 20th century, researchers focused almost exclusively on predicting gender differences in STEM success from single skills, such as math ability (Hyde, 2014). It was only at the end of the 20th century, after decades of data on standardized tests had accumulated, that evidence suggested the gender differences were rapidly closing for many cognitive abilities, including math ability (Feingold, 1988). Recent representative studies and meta-analyses reinforce this result, showing that gender gaps in overall math performance have dropped to trivial differences: studies of over 7 million students in state math assessments indicate gender differences of only $d = 0.0065$, meaning the averages of men and women on math assessments are almost perfectly overlapping (Hyde, Lindberg, Linn, Ellis, & Williams, 2008). And a meta-analysis of 242 studies shows a mere difference of $d = 0.05$ on math performance, again indicating almost perfect overlap of men and women's average performance (Lindberg, Hyde, Petersen, & Linn, 2010). The weight of the evidence therefore implies gender parity in math ability (Hyde, 2014, 2016; Zell, Krizan, & Teeter, 2015).

In response, some researchers and public officials have argued that, while gender differences have disappeared in average mathematics ability (i.e., the middle of the distribution), men nevertheless remain overrepresented as high-performers (i.e., right-tail of the distribution; Ceci et al., 2014). On the one hand, nationally-representative samples indeed reveal slight but consistent advantages for boys on standardized math tests, with a 2:1 overrepresentation among math high-performers from kindergarten (Penner & Paret, 2008) to grade 7 (Wai, Cacchio, Putallaz, & Makel, 2010). On the other hand, these same studies reveal that the gender gap in high-performers has closed rapidly over time, moving from 13.5:1 in the 1980s, to 3.8:1 in the 1990s, to 2:1 today (Penner & Paret, 2007; Wai et al., 2010). This rapid closing of the gap on both average and high-performing math ability (Hyde, 2014; Wai et al., 2010) challenges the assumption that differences are rooted in immutable traits.

Additionally, gender differences in both average and high-performing math ability vary greatly across cultures (Else-Quest, Hyde, & Linn, 2010; H. Gray et al., 2019), across U.S. states (Pope & Sydnor, 2010), and across ethnic groups (Hyde & Mertz, 2009; Penner & Paret, 2008), providing evidence of mutability based on local contexts. Finally, gender differences in math performance are most notable when gender stereotypes are activated prior to a test: creating stereotype threat by framing a math test as "known to show gender differences" impairs females' performance relative to framing the same test as "not showing gender differences" (Nguyen & Ryan, 2008; Spencer, Steele, Quinn, et al., 1999; but see Stoet & Geary, 2012). This further highlights the role of mutable beliefs rather than immutable biological traits as the most likely explanations of historic gender differences in math performance. Thus, there remains no compelling evidence that gender differences in math ability are immutable or biologically innate (Ceci et al., 2014; Ceci & Williams, 2010; Hyde, 2016; Spelke, 2005).

Moreover, even an overrepresentation of 2:1 among math high-performers would not be sufficient to account for the nearly 5:1 disparity seen in the representation of senior faculty in STEM fields (Table 2), the 7:1 disparity seen in first vs. last authorship rates for some fields (Table 4), or differences in median salaries (Table 3). Other factors must therefore contribute, such as gender differences in academic self-efficacy (Dixson, Worrell, Olszewski-Kubilius, & Subotnik, 2016) or math confidence (Flanagan & Einarson, 2017). In sum, because gender differences in math ability (1) produce small to non-existent effects, (2) are disappearing over time, and (3) cannot fully explain the large and persistent gaps, it can no longer be said that women and men are treated differently in STEM because of different cognitive capacities in mathematics. Recognizing this conclusion, researchers have turned to examining other abilities that may contribute to gender differences in STEM.

Two additional skills relevant to STEM success are spatial and language ability, and both show consistent gender differences (Halpern et al., 2007). On many tests of spatial cognition, especially those involving 3D mental rotation tasks, men significantly outperform women, with a meta-synthesis of 70 meta-analyses revealing that men are approximately ½ a standard deviation above women (d = 0.57; Zell et al., 2015). However, even on 3D rotation tasks, gender differences fluctuate as a function of subject age, testing format, and test framing (Huguet & Régner, 2009; Voyer, 2011; Voyer et al., 1995), with reversals to female advantages even observed when mental rotation tasks are framed as “art tasks” rather than “math tasks” (Huguet & Régner, 2009). Furthermore, other aspects of spatial cognition reveal female advantages (e.g., object identity memory), or no gender differences (e.g., object location memory, Voyer, Postma, Brake, & Imperato-McGinley, 2007).

In contrast to spatial cognition, language skills appear to consistently favor women (Halpern et al., 2007; Hyde & Linn, 1988; Miller & Halpern, 2014). Recent estimates from national assessments document female advantages of approximately ¼ of a standard deviation (d = -.27) for reading and ½ a standard deviation (d = -.54) for writing (Reilly, Neumann, & Andrews, 2018). Moreover, gender gaps in language ability have not shown significant change from 1988-2011 (Reilly et al., 2018). This implies that the causes of language differences – whether biological, as suggested by the overrepresentation of men with reading impairments (Halpern, Beninger, & Straight, 2011; Rabiner & Coie, 2000), and/or socio-psychological, as suggested by the sex-typing of language abilities as “female” (Halpern, Straight, & Stephenson, 2011;

Marinak & Gambrell, 2010) – have remained stable over time, unlike closing gaps for other abilities.

Although often overlooked, the role of reading and writing are arguably just as relevant to STEM as math or spatial skills. The ability to comprehend verbal material and to communicate effectively through writing and speaking are obvious components of success in publications, grants, presentations, and effective STEM teaching or leadership. Indeed, long-term success in STEM careers is likely to be predicted by a set of skills, including abilities in language, spatial rotation, math, and more (Ackerman, Kanfer, & Beier, 2013). It is therefore worth focusing on the diversity of skills available within an individual rather than emphasizing any single quality.

Differences in Preferences, Values, or Lifestyle Choices

The cause of gender disparities in STEM has increasingly been linked to gendered roles, values, and lifestyle preferences (Ceci et al., 2014; Ceci, Williams, & Barnett, 2009; Ceci & Williams, 2011). In particular, the "goal congruity hypothesis" (Diekman et al., 2010) was so-named to capture the idea that women make the choice, from both sociocultural pressures and innate psychological orientations, to opt out of STEM because they perceive their gendered goals to be incongruent with the nature of STEM work, the opportunities available in STEM, and their likelihood of success. Simply, women perceive a mismatch between their goals/values and the STEM environment.

These values are argued to arise early in childhood, when boys and girls experience both social pressures and possibly innate inclinations to occupy different roles: boys are expected to (and, on average, do) prefer activities that are competitive and active, while girls are expected to (and, on average, do) prefer activities that are communal and involve helping (Eagly, 1987). These early-formed values cascade into later life, with women more likely to endorse communal, group-serving, people-oriented, family, and altruistic values, and men more likely to endorse agentic, self-serving, thing-oriented, money, and status values (Diekman et al., 2010; Ferriman, Lubinski, & Benbow, 2009; Su, Rounds, & Armstrong, 2009; Weisgram, Dinella, & Fulcher, 2011).

Simultaneously, STEM environments are perceived, on both explicit self-reports and indirect implicit measures, to be environments that endorse power, status, competitiveness, and isolation (Diekman, Clark, Johnston, Brown, & Steinberg, 2011). Such qualities are therefore viewed as incompatible with the communal group-serving values that women (more than men) appear to endorse (Diekman, Weisgram, & Belanger, 2015). Analogously, evidence points to men avoiding communal group-serving environments (e.g., healthcare, early education, and domestic work) because these careers are viewed as incompatible with both the status-based and self-serving values that men (more than women) appear to endorse (Block, Croft, & Schmader, 2018).

As a consequence of such mismatch between values and environments, women may be particularly likely to opt out of (and men particularly likely to opt into) subfields that are perceived to strongly endorse the "brilliance," status, and competition (i.e., mathematics, engineering and computer science), thereby accounting for differences in representation across subfields (e.g., Leslie, Cimpian, Meyer, & Freeland, 2015; Meyer, Cimpian, & Leslie, 2015). Additionally, women may be more likely to select low-paying part-time positions to better facilitate family goals, whereas men may be more likely to select high-paying status-based positions, possibly contributing to the gender pay gap. Women may also be more likely to perform service activities to satisfy communal group-serving values, whereas men may be more likely to focus on research activities to satisfy agentic self-serving values, contributing to disparities observed in service vs. research awards. The match between values and environments (i.e., goal congruity) may therefore play a role in explaining gender gaps across representation, pay, and recognition.

Yet the question remains whether STEM environments are inherently incompatible with values that women are more likely to endorse, or whether generations of male-dominated STEM environments have led to a perception of incompatibility. If it is more about historical perceptions, then increasing the perception that a STEM environment can satisfy group-serving values should correspondingly increase women's success and persistence in STEM.

Indeed, describing STEM tasks and careers as emphasizing communal group-serving values (Diekman et al., 2015), helping (Weisgram & Bigler, 2006), or dedication (Bian, Leslie, Murphy, & Cimpian, 2018), rather than competition, isolation, or brilliance, increases women's interest in pursuing and persisting in STEM. For example, when female general population participants read about a STEM internship or major that emphasizes dedication (vs. brilliance), they are approximately ½ a standard deviation more likely to report interest (Bian et al., 2018). Similarly, females in college are found to be more likely to feel like they belong in STEM after subtle environmental cues that emphasize STEM stereotypes of isolation or competition (e.g., Star Trek posters) are removed (Cheryan, Plaut, Davies, & Steele, 2009). Thus, the goal mismatch appears to be rooted in perception rather than inherent features of STEM environments. As such, it is important to examine where this perception comes from (Cheryan, Ziegler, Montoya, & Jiang, 2017), especially the role of implicit and explicit biases in shaping perceptions of beliefs, values, and the environment.

2.1 Explicit and Implicit Bias

Beliefs and stereotypes that associate men, more than women, with science, math, leadership, or careers have long been documented on explicit, self-report measures and representative polls (General Social Survey, 2019). Yet self-reports are limited in that respondents may be unwilling to state their full beliefs (for fear of appearing biased), and/or may be unable to state their full beliefs (because of limited introspective access to one's own mind, Greenwald & Banaji, 1995). Recognizing these limitations, researchers have argued that biased beliefs can exist at both an explicit and implicit level – the latter being relatively more automatic, less conscious, and less controllable than the former. The most widely-used measurement of implicit biases, the Implicit Association Test (IAT, Greenwald, McGhee, & Schwartz, 1998), uses response latencies to indirectly capture the overlap between concepts such as "male" and "science" versus "female" and "arts."

Implicit and explicit biases are related but distinct psychological constructs (Nosek & Smyth, 2007). For instance, while a person responding to a survey may explicitly say that they believe both men and women are capable in science, the same person may nevertheless show faster responses when pairing male-science (and female-arts) words compared to when pairing male-arts (and female-science) words, suggesting that they hold implicit beliefs linking men (more than women) with science over arts. Crucally, explicit and implicit biases both contribute to predicting behaviors and outcomes (Kurdi et al., 2018) and are therefore both necessary to understand the operation of bias in STEM. Moreover, given the general disappearance of explicit bias against women in STEM (General Social Survey, 2019), it would be difficult to explain the slowness of change in women's representation and success without considering the possibility that biased gender perceptions and evaluation may also emanate from mental operations outside conscious control.

To understand the possible role of implicit and explicit biases in STEM gender disparities, the extent of these biases needs to be examined. If implicit biases are only identified, for example, in older adults, men, or those from particular geographic regions, then the biases are unlikely to play a role in accounting for widespread gender gaps in STEM. If, however, implicit biases are found to be persistent and pervasive, then their role within STEM becomes more meaningful. Over two decades of research on implicit gender stereotypes has conclusively shown that gender biases in STEM are indeed prevalent across the lifespan, across genders, across nations, and across time.

Implicit gender bias across the lifespan. Implicit gender-STEM stereotypes are documented from the earliest ages tested: by at least 6 years of age, both boys and girls implicitly associate math with boys more than with girls (Cvencek, Meltzoff, & Greenwald, 2011). Even in Singapore, a country where girls excel in mathematics, implicit stereotypes of boys=math/girls=reading are similarly early-emerging for both boys and girls (Cvencek, Meltzoff, & Kapur, 2014). This is striking as it suggests that biased beliefs may emerge even in the absence of evidence. At the same ages, children also endorse explicit stereotypes, including the belief that math is more for boys than girls (Cvencek et al., 2011), and that boys, more than girls, are "really, really smart" (Bian, Leslie, & Cimpian, 2017).

New analyses of nearly 300,000 respondents from the Project Implicit Demonstration website (http://implicit.harvard.edu) extend these findings through adolescence and adulthood, providing similar conclusions of early-emergence (Figure 3). By elementary and middle school (respondents under 14 years old), 58% of respondents already show a strong, moderate, or slight implicit stereotype that men=science/women=arts, while only 17% show an opposite stereotype of women=science/men=arts and 25% show a neutral association, as measured by the IAT.

Notably, the strength of the implicit men=science/women=arts association increases slightly through the later lifespan: 68% of high schoolers, 71% of college students, 68-69% of early-career respondents (ages 22-40), 72-74% of mid-career respondents (ages 40-55), and 77% of older respondents (ages 55+) show implicit men=science/women=arts associations, with similar age-related trajectories in both women and men. Although these data are cross-sectional (making it difficult to disambiguate an age effect from an effect of historical changes over time), the increasing stereotype strength across ages nevertheless mirrors the trends of increasing underrepresentation from high school to college to full professorships. Age-related increases in stereotype strength may therefore represent either a cause and/or consequence of increases in gender disparities across career trajectories.

Figure 3. Implicit men=science/women=arts stereotypes across the lifespan, by gender. Data retrieved from the Project Implicit Demonstration Website. See https://osf.io/n9jca/ for raw data and code.

Implicit gender bias across genders. Surprisingly, women and men hold similarly strong implicit gender-STEM stereotypes. Data from Project Implicit show that, overall, 69% of women and 72% of men express slight, moderate, or strong implicit men=science/ women=arts associations (see also Nosek et al., 2007). Nevertheless, gender differences in implicit stereotypes emerge among scientists from particular STEM subfields (Nosek & Smyth, 2011; Smeding, 2012; Smyth & Nosek, 2015): women employed in male-dominated subfields (e.g., math or engineering) express significantly weaker implicit men=science/women=arts stereotypes than men in those subfields, whereas women employed in female-dominated subfields (e.g., humanities) express significantly stronger stereotypes than men in those subfields. This suggests that women already in science may perceive science as equally applicable to women and men, perhaps as a consequence of their own identification with science (e.g., Nosek, Banaji, & Greenwald, 2002), or being exposed to more female scientist role models (Dennehy & Dasgupta, 2017). In contrast, women outside of science may neither identify with science nor be exposed to the same frequency of female scientists and may therefore associate STEM more with men than women. However, it is worth emphasizing that even women already in science still hold an implicit stereotype of men=science/women=arts (Smyth & Nosek, 2015), implying that identification alone may not be sufficient to override pervasive cultural stereotypes.

Implicit gender bias across countries. In every country where the IAT has been used, there is an association of men=science/women=arts (Miller, Eagly, & Linn, 2015; Nosek et al., 2009). No country shows the opposite association. Yet despite this widespread prevalence, there is also meaningful variability. Nation-level differences in the strength of implicit gender-science stereotypes are correlated with nation-level differences in gender gaps on national 8^{th} grade math and science assessments (Nosek et al., 2009), as well as nation-level differences in gender gaps in STEM representation (Miller et al., 2015). These results are important because they highlight (1) that implicit gender-science stereotypes are not necessarily innate or inherent, since they vary across countries, and (2) that implicit gender-science stereotypes can help explain gender disparities in STEM, since variability in stereotypes correlates with variability in STEM achievement and representation.

Implicit gender bias across time. Explicit gender stereotypes and attitudes against working women and female scientists have decreased markedly over the past several decades (CNN, 2012; General Social Survey, 2019; Huang, Osborne, & Sibley, 2018). Yet absence of bias has not been achieved: even on self-reported attitudes and beliefs, 25% of U.S. respondents in 2018 agreed or strongly agreed that it was better for a a man to work and a woman to stay home (General Social Survey, 2019). Moreover, subtle biases are even more persistent, with women still perceived as "warm" but "incompetent" (Fiske, 2018; Haines, Deaux, & Lofaro, 2016), and still described with words such as "caring" and "emotional," rather words such as "competent" or "intelligent" (Garg, Schiebinger, Jurafsky, & Zou, 2017). While some progress has been made, gender bias continues in both explicit and subtle ways.

In line with this simultaneous progress and stability, new analyses of the Project Implicit dataset examining change in implicit men=science/women=arts stereotypes from 2007-2016 reveal that implicit gender stereotypes have decreased by approximately 16% overall (comparable to change in implicit race and skin-tone attitudes, Charlesworth & Banaji, 2019b). Crucially, however, this change appears to be largely isolated to women (whose implicit bias has decreased by 19%), with relatively little change observed among men (decreased by only 6%, Figure 4). This result is unique, as almost every other implicit attitude or stereotype shows parallel change between men and women; there appears to be a particular intransigence among men's implicit gender-science stereotypes. Moreover, although overall trends of change in implicit gender stereotypes are both surprising and encouraging, the biases remain far from neutrality and suggest relative persistence over time.

Figure 4. Change over time in implicit men=science/women=arts stereotype, by gender (2005-2017). Weighted monthly means (weighting to control for sample change over time) are plotted in thin gray (for men) and black lines (for women). Decomposed trend lines (removing seasonality and random noise) are plotted in thick gray (for men) and black lines (for women). Data retrieved from the Project Implicit Demonstration Website. See https://osf.io/n9jca/ for raw data and code; see (Charlesworth & Banaji, 2019b) for further details on analysis method including controls for alternative explanations such as sample change over time.

In sum, implicit gender-science stereotypes are present across the lifespan, in both men and women, in every nation, and across time. Such persistence and prevalence in implicit biases match the prevalence of gender disparities in STEM representation, pay, and recognition.

Together, these data reinforce (1) that gender-science stereotypes exist both in explicit statements and on implicit measures that tap less controllable beliefs, (2) that gender-science stereotypes are not isolated to some people in only some parts of the world but, rather, are widespread, and (3) that this pervasiveness, as well as variability within and across regions, provides an opportunity for deeper theoretical understanding of the mechanisms behind gender disparities in STEM.

The operation of implicit and explicit gender biases in STEM. If implicit and explicit biases indeed play a causal role in gender disparities in STEM, how would one know? What would evidence for bias look like? Complementary sources of evidence would be most persuasive. First, if bias is operating, then observational evidence of gender disparities (e.g., data on representation, pay, and awards/recognition) should reveal persistent disparities even after alternative explanations or correlated variables are accounted for (e.g., subfield, part-time versus full-time job status). For example, the aforementioned 9% pay gap that persists after controlling for alternative explanations implies that an additional causal mechanism (i.e., bias) may be operating.

Second, if bias is operating, then correlational evidence should reveal a relationship between the magnitude of gender disparities and the magnitude of implicit or explicit gender stereotypes. This is suggested, for example, in the finding that larger gender gaps on national science and math assessments are positively correlated with stronger implicit gender-science stereotypes on the IAT, even after controlling for explicit stereotypes and alternative explanations (Nosek et al., 2009).

Third, the strongest evidence for bias is experimental. In particular, experimental resume and audit studies can show that identical candidates (with the same resume and qualifications) receive differential treatment exclusively due to gender, and that the extent of such differential treatment is predicted by evaluators' explicit and implicit gender stereotypes. With these three standards of evidence, the possible operation of bias is examined in (1) hiring and compensation, (2) grants, publications and awards, and (3) organizational and academic culture.

Hiring and compensation. Evidence for the operation of gender biases in hiring and compensation comes primarily from experimental audit studies showing that women applicants in STEM are less likely to be hired and also receive lower starting salaries than men with identical records (Milkman, Akinola, & Chugh, 2015; Moss-Racusin, Dovidio, Brescoll, Graham, & Handelsman, 2012; Reuben, Sapienza, & Zingales, 2014; Steinpreis, Anders, & Ritzke, 1999; but see Williams & Ceci, 2015). To illustrate one such study, Moss-Racusin and colleagues (2012) asked faculty from biology, chemistry, and physics to evaluate the application of a prospective lab manager on their hire-ability, competence, suggested salary, and deservingness of mentoring. Candidates' applications were identical with the exception of whether the candidate's name was female or male.

Six results from this study are notable: (1) despite identical resumes, the female candidate was perceived as less hire-able than the male candidate; (2) the female candidate was offered the equivalent of 88% of the male candidate's salary; (3) the female candidate was perceived to be less deserving of mentoring than the male candidate; (4) both male and female faculty evaluators were more likely to select and more generously compensate and mentor male candidates; (5) the extent of differential evaluation was mediated by the perception of greater competence in male than female candidates; and (5) the extent of this perceived competence gap was, in turn, moderated by the strength of faculty's subtle gender bias (measured via self-reported modern sexism or beliefs that are benevolent but paternalistic; Swim, Aikin, Hall, & Hunter, 1995).

Together, these findings highlight the operation of subtle gender biases as a mechanism behind hiring, compensation, and mentoring disparities (Moss-Racusin et al., 2012).

Importantly, implicit biases measured through the Implicit Association Test (IAT) have also been shown explain such gender disparities. For instance, Reuben and colleagues (2014) asked participants ("employers") to hire a candidate for a simple math task, and were given a choice between two candidates who were matched on performance but not gender. Further, in some conditions, employers were given information about the candidates' past performance on the math task. The results provide three noteworthy conclusions. First, when employers had no information other than the candidates' gender, the employers (both male and female) were half as likely to hire the female candidate than the male candidate, implying a baseline preference for males over females. Second, this gender-biased hiring was reduced, but not eliminated, when employers were given information about the two candidates' identical past performance, indicating that the employers were not sufficiently updating their beliefs. That is, if employers had sufficiently updated following evidence of equivalent performance, then hiring should also have been equivalent between male and female candidates. Third, both the extent of the initial hiring bias and the extent of the updating bias were correlated with employers' implicit stereotypes associating men=math & science/women=liberal arts. Thus, implicit bias may help explain not only initial gaps in hiring and representation but also the persistence of these gaps even in the face of evidence showing women's capacities and success in STEM.

Large-scale correlational data are consistent with these experimental findings. On explicit measures of bias, the greater the number of academics in a STEM field who endorse the beliefs that (1) brilliance (rather than dedication) is required for success, (2) men are more brilliant than women, and (3) women are not suited to scholarly work, the lower the representation of female faculty in those fields (Leslie et al., 2015; Meyer et al., 2015). Similarly, the higher the endorsement of an explicit association between science and male, the lower the number of female faculty in that field (Smyth & Nosek, 2015). Importantly, these correlations between representation and explicit stereotypes remain significant after controlling for proxies of personal values (e.g., perceived selectivity/competitiveness of the field, working part-time vs. full-time to satisfy family values). Thus, the role of bias may persist above values and lifestyle choices.

Women's representation in STEM is also correlated with implicit measures of gender bias. First, the more men majoring in a STEM field express the implicit men=science/women=arts stereotype, the lower the number of women in that field (Smyth & Nosek, 2015). Second, the more a nation expresses the implicit men=science/women=arts stereotype, the lower the number of women in STEM in that nation (Miller et al., 2015). Third, the more a field describes professors with traits of brilliance and genius (as measured indirectly through language in teaching evaluations), the lower the number of women in that field (Storage, Horne, Cimpian, & Leslie, 2016). Again, statistically significant correlations between implicit stereotypes and representation remain after controlling for measures of mathematics aptitude, field selectivity, or hours worked (i.e., part-time/full-time), again suggesting a role for bias above alternate explanations such as ability or values.

Nevertheless, evidence from these experimental and correlational studies needs to be reconciled with data from the National Science Foundation, the National Center for Education Statistics, and faculty surveys reporting that, from 1995-2003, women applying for professorships in STEM were hired at rates commensurate to their application rate, implying no hiring biases (National Academy of Sciences, 2010). Additionally, a recent audit study suggests that, in fields of biology, psychology, and engineering, women appear to have a 2:1 advantage in hiring for tenure-track positions (Williams & Ceci, 2015).

Explaining such discrepancies will likely require many factors, including (1) changes over time in the focus on equitable hiring practices and pro-active efforts to reconcile past gender disparities (leading earlier studies to show more bias than later studies), (2) experimental differences in the measured outcomes (e.g., hiring a lab manager vs. evaluating a candidate for a math task vs. hiring a tenure-track faculty) and the fields studied (e.g., psychology vs. engineering), and/or (3) applicant differences (e.g., women may have a higher threshold and be more self-selective for applying to jobs; Ceci et al., 2014). Continued research is needed to resolve correlational, experimental, and observational evidence, as well as to understand disproportionately lower hiring rates and compensation of mothers, racial minority women, women in high-status positions, and women in engineering and computer science.

Publications, grants and awards. Observational evidence, reviewed in Part One, suggests the encouraging result of overall gender parity in authorship, grants, and awards in STEM. Nevertheless, subtle gender differences persist on indicators such as (a) last authorship positions (Holman et al., 2018), (b) application rates for the top 1% of grants (Hosek et al., 2005), and (c) rates of research versus service awards (Metcalfe, 2015; Popejoy & Leboy, 2018). While these data suggest the operation of bias because gender disparities persist after accounting for alternative explanations, compelling experimental evidence for the operation of implicit and explicit biases in publications, grants, and awards remains limited (Eagly & Miller, 2016).

With respect to gender bias in academic publications: audit studies indicate that publications, conference abstracts, and fellowship applications from men are more likely to be accepted, rated as higher quality and indicating more competence, and given more collaboration interest than quality-matched materials from women (Knobloch-Westerwick, Glynn, & Huge, 2013; Krawczyk & Smyk, 2016; Wenneras & Wold, 1997). These few studies imply that subtle disparities in publications may arise from biased evaluations from peer reviews.

On the other hand, removing gender (i.e., by masking the author's gender through double-blind reviews) does not appear to increase the rate of publication success for women (Tomkins, Zhang, & Heavlin, 2017; Webb, O'Hara, & Freckleton, 2008). While it is possible that the lack of efficacy in double-blind review is due to men producing better publications (for many reasons including differences in caregiving demands, or differences in risk-taking with "big" research ideas), it may be more likely due to the fact that author gender can be detected even without the author's gendered name. Indeed, author gender could be determined using cues such as style of writing (Argamon, Koppel, & Fine, 2003), word use (Kolev, Fuentes-Medel, & Murray, 2019), and overall tendency to self-cite (Eagly & Miller, 2016). Thus, reviewers' implicit or explicit biases may be able to persist even under double-blind conditions because the reviewers can still detect author gender.

The operation of gender bias in grants and awards has also received limited experimental study. One recent experimental audit study shows no evidence of gender bias in initial grant reviews at NIH (Forscher et al., 2019). Additionally, a review screening 170 papers identified only one study that directly assessed the effect of gender bias in grant review (Tricco et al., 2017). This study found that removing gender through double-blinding did not increase the proportion of women's successful grant applications (Ledin, Bornmann, Gannon, & Wallon, 2007), although (as aforementioned) double-blind conditions may not entirely eliminate evaluators' ability to detect applicants' gender and the conclusions are therefore limited.

Finally, to our knowledge, there remains no experimental evidence that directly measures the role of implicit or explicit biases in the persistent gap in research versus service awards (Lincoln et al., 2012; Popejoy & Leboy, 2018), suggesting an important focus for future research. While numerous cognitive biases (e.g., shifting standards, halo effects, confirmation bias) are likely to disrupt objectivity in the review of publications, grants, and awards (Kaatz, Gutierrez, & Carnes, 2014), further research is needed to experimentally quantify the role of such biases.

Organization and academic culture. Beyond disparities of representation, compensation, and recognition, implicit and explicit biases may also operate in the experiences of the organization and academic culture. Gender differences in experiences of a hostile culture have received increasing attention through the #metoo movement and highly-publicized allegations of harassment. Large-scale empirical reports also indicate that hostile culture is a persistent and pervasive problem: at least half of all female academics in STEM (versus 19% of male academics in STEM) report experiencing sexual harassment, and even greater numbers (78%) of females in male-dominated STEM workplaces report experiencing gender-based discrimination (Funk & Parker, 2018; National Academies of Sciences Engineering and Medicine, 2018).

The operation of bias in producing these gender differences in organizational experiences is suggested by audit studies showing that a female scientist is offered less mentorship relative to an identical male scientist as a result of the evaluators' biases (Correll et al., 2007; Moss-Racusin et al., 2012). This decreased mentoring may, in turn, hamper female scientists' feelings of belonging and identification and exacerbate feelings of a hostile climate. Indeed, women in STEM are more likely than men to report a lack of belonging (Cheryan & Plaut, 2010; Cheryan et al., 2017; McPherson, Park, & Ito, 2018), a lack of support and free expression (Xu, 2008), a lack of mentorship and role models (Cheryan & Plaut, 2010; Cheryan, Siy, Vichayapai, Drury, &

Kim, 2011), and a lack of feeling identified with or competent in STEM (Ertl, Luttenberger, & Paechter, 2017; Spencer, Steele, & Quinn, 1999), including on implicit measures (Nosek et al., 2002).

Finally, correlational studies show that the extent of reported gender-based harassment in an academic field is correlated with the strength of men's implicit gender stereotypes in that field, as both gender-based harassment and implicit gender stereotypes are greatest in male-dominated fields (Dresden, Dresden, Ridge, & Yamawaki, 2018; see also Smyth & Nosek, 2015). Thus, although no direct experimental evidence can be offered for the operation of bias in producing hostile organizational climates, correlational data, audit studies on mentoring, and observational data on belonging, together suggest a possible role for implicit and explicit biases that is worthy of attention (Funk & Parker, 2018; National Academies of Sciences Engineering and Medicine, 2018).

Part Three: How? Proposed Solutions to Gender Disparities in Science

When faced with the type of data presented in Parts One and Two, nearly every STEM organization has had to consider the ways to address the biases, both inside and outside women themselves, that limit women's full participation in STEM (Corbett & Hill, 2015; Hill et al., 2010; Lebrecht, Bar, Barrett, & Tarr, 2012; National Academy of Sciences, 2006, 2010; National Science Foundation National Center for Science and Engineering Statistics, 2017; Valantine & Collins, 2015). Crucially, because the issues of gender in STEM involve human beliefs and decision-making that seem familiar to all individuals, there are often well-intentioned interventions based only on personal experiences or intuitions and not grounded in evidence or routine evaluations. Such approaches may backfire. For example, Dobbin and Kalev (2013) showed that most diversity training implemented from the 1960s to the early 2000s had either no impact or even slightly reduced the diversity of the workforce (see also, Paluck & Green, 2009). Addressing gender bias in STEM should therefore be treated with rigorous evidence, as would be expected of any other STEM project (Kang & Kaplan, 2019). This section provides a brief review of recent and rigourous evidence-informed and evaluated interventions that focus on reducing gender disparities in STEM by changing individual minds/behavior (i.e., individual-level gender bias) or organizational cultures/practices (i.e., organization-level gender bias).

3.1 Changing Individual-Level Gender Bias

Individual-level bias emerges in both "perceivers" (e.g., individuals making decisions about a person at the time of recruiting, hiring, or promoting), as well as in "targets" themselves (e.g., women's and men's own beliefs about themselves in STEM). Individual-level interventions therefore differ in whether they focus on reducing the biases of perceivers or targets.

First, to reduce the biases of perceivers, and to increase their willingness to promote change, interventions using a "habit-breaking" approach have been shown to effectively reduce both racial and gender biases (Carnes et al., 2015; Devine, Forscher, Austin, & Cox, 2012; Devine et al., 2017; Forscher, Mitamura, Dix, Cox, & Devine, 2017). These interventions assume that implicit biases are like "habits." As such, bias is best addressed by making participants aware of the biased habits they may have through education on the science of implicit bias and its consequences for behavior. After promoting bias awareness, participants in the "habit-breaking" intervention are equipped with strategies argued to reduce bias in the mind. For example, participants are taught techniques such as "putting oneself in another's shoes" (perspective-taking), thinking of people from other groups as individuals rather than just as homogenous group members (individuation), and generating examples of people from other groups who challenge stereotypical assumptions (e.g., Marie Curie; counterstereotype exposure). While some of these strategies have shown mixed effects when implemented in isolation – especially perspective-taking (Catapano, Tormala, & Rucker, 2019), and intergroup contact (Paluck, Green, & Green, 2018) – the combination of strategies, coupled with the educational approach, show promise in addressing gender disparities in STEM.

To illustrate: in a cluster-randomized-controlled trial of 92 STEM departments, faculty members in departments that received the 2.5 hour “habit-breaking” workshop reported more awareness of implicit bias and more actions to promote gender equity, even after a delay of three months (Carnes et al., 2015). These individual-level changes also trickled up into organization-level changes in both culture (with greater experiences of belonging reported by both men and women; Carnes et al., 2015), and practices (with more gender-equitable hiring; Devine et al., 2017). Indeed, while the number of women hired in control departments remained unchanged over two-years, the number of women hired in intervention departments increased by 18%. Thus, “habit-breaking” appears to have real-world effectiveness in STEM.

Although promising, the habit-breaking intervention nevertheless requires a relatively large time commitment and trained educators. As such, it may not be easily and widely applied across organizations. Partly to address scalability, the Video Interventions for Diversity in STEM (or VIDS, https://academics.skidmore.edu/blogs/vids/) adopt similar approaches to the “habit-breaking” interventions by promoting gender bias literacy through freely-available videos consisting of six 5-minute presentations, each discussing the results of a peer-reviewed study on gender bias. VIDS has been found to successfully reduce explicit gender biases, increase awareness of everyday bias, and increase self-efficacy to confront bias among both general public and academic faculty participants (Hennes et al., 2018; Moss-Racusin et al., 2018; Pietri et al., 2017), and may be applicable for many organizations.

Finally, interventions using evidence-based confrontation, in which participants are provided with objective, personalized evidence of having exhibited gender bias in evaluations, have also shown some effectiveness in reducing perceivers biases (Parker, Monteith, Moss-Racusin, & Van Camp, 2018). Specifically, these interventions have been found to increase participants negative self-directed affect (e.g., guilt) and, as a consequence, increase participants' concern about, and intentions to control, future bias. However, confrontation interventions also produce defensiveness (Parker et al., 2018) and, without labor-intensive personalization, are often dismissed (Gulker, Mark, & Monteith, 2013). Additionally, they appear to be less effective in changing the biases of men than women (Handley, Brown, Moss-Racusin, & Smith, 2015; Moss-Racusin, Molenda, & Cramer, 2015). Given the dominant presence of men in STEM, this lower efficacy for men is a non-trivial concern, and evidence-based confrontations may therefore need further study.

Beyond the biases of the perceivers, there is also a role for the self-defeating perceptions, attitudes, and beliefs held by those in underrepresented groups (e.g., women themselves, Jost & Banaji, 1994; Jost, Banaji, & Nosek, 2004). To this end, interventions have focused on increasing identification, belonging, and persistence among the targets of discrimination. With this goal, promising interventions have found that contact with female (vs. male) peers, professionals, and teachers improves women's implicit identification with STEM, as well as greater self-efficacy and more effort on STEM tests (Stout, Dasgupta, Hunsinger, & McManus, 2011). Indeed, even a one-hour interaction with a female role-model in STEM increases the probability that Grade 12 students in France will enroll in a selective male-dominated STEM class by up to 30% (Breda et al., 2018). And a single letter from a female role-model can improves course grades and reduces dropout among U.S. introductory psychology and chemistry students (Herrmann et al., 2016).

Crucially, in contrast to the assumption that women can only achieve benefits from female role models (which inadvertently places an additional service burden on female mentors), the gender of the role model appears to be less important than their ability to challenge stereotypes (Cheryan et al., 2011; Fuesting & Diekman, 2017). For example, if a male role model challenges STEM stereotypes (e.g., by wearing a plain t-shirt rather than a t-shirt reading "I code therefore I am", or expressing that they like to hang out with friends rather than that they like to watch anime), the counterstereotypical male role model appears to be just as helpful as a female role model in promoting women's beliefs about success in STEM (Cheryan et al., 2011). Encouraging the wide adoption of these simple counterstereotypical signals among both male and female faculty may therefore be an actionable step to help foster women's own success beliefs in STEM.

3.2 Changing Organization-Level Gender Bias

STEM environments exhibit biases that have consequences for women's safety, performance, and perceived belonging (see section 2.3). While much of this hostile climate comes from the accumulation of individual biases, a climate is also grounded in structural features, ranging from the possibility of flexible work arrangements (Fuller & Hirsh, 2018), to the presence of stereotype-reinforcing decorations in physical spaces (Cheryan et al., 2009). Allowing flexible work arrangements in STEM can have beneficial effects on the treatment and advancement of women (particularly mothers) because the arrangements both endorse and facilitate communal and family values. Although there are stigmas surrounding flexible work arrangements (e.g., Cech & Blair-Loy, 2014), the benefits appear to outweigh these costs: indeed, flexible work can reduce the wage gap for mothers by reducing within-organization disparities and allowing mothers to enter high-wage establishments (Fuller & Hirsh, 2018). Given that female junior faculty with children and working partners spend 20 hours more per week on household and childcare duties than their male counterparts (Harvard University Office of the Senior Vice Provost, 2014), focusing on reducing or supporting women's household and childcare duties may be crucial to ensuring equal advancement in STEM.

Large-scale organizational change, such as implementing flexible work policies, can often be slow. These changes can therefore be supplemented by more immediate interventions to improve the ongoing experiences of women in STEM. For instance, as discussed in section 2.2, improvements in both men and women's belonging in STEM can be achieved by removing cues of masculine stereotypes in classrooms (e.g., Star Wars posters; Cheryan et al., 2009).

Similarly, increasing the perception that STEM environments can satisfy group-serving values – such as by emphasizing the daily tasks of scientists that involve mentorship or helping – leads female college students to report more interest and investment in STEM careers (Diekman et al., 2011). Changing such subtle linguistic cues can also have positive outcomes on self-reported STEM interest for children as early as elementary and middle school (Colvin, Lyden, & León de la Barra, 2013; Rhodes, Leslie, Yee, & Saunders, 2019; Tyler-Wood, Ellison, Lim, & Periathiruvadi, 2012; Weisgram & Bigler, 2006). It is these types of changes (e.g., emphasizing the opportunities of group-serving values) that are anecdotally described to lead to milestone achievements, such as the recent success of women composing an impressive 48% of Carnegie Mellon's incoming 2016 computer science class (Spice, 2016). While we may take for granted how we describe and decorate STEM environments, reducing the subtle stereotypicality in environments can improve women's self-reported feelings of belonging and interest in STEM.

As such, critically evaluating and, if necessary, changing our own organizations and workplaces (including job postings or office decorations) may be a small but effective action to promote gender equity.

The emerging trends in interventions to reduce individual and organizational gender biases are promising. However, additional research is needed (1) using both lab-based experiments and randomized-control-trial designs in the field, (2) assessing implicit and explicit stereotypes as both outcomes and mediators of behavior change, (3) looking at differences across STEM subfields, and (4) addressing intersectional biases towards minorities and mothers. Additionally, research that identifies the overarching characteristics of successful interventions is crucial (Dobbin & Kalev, 2013; Moss-Racusin et al., 2014; Paluck & Green, 2009). At present, it appears that, regardless of the target (individual or organizational), interventions are more effective when they (1) are grounded in theory and evidence, (2) involve active learning and responsibility rather than lecturing or forced training, (3) avoid assigning personal blame or guilt, and (4) include evaluation plans of intervention efficacy (Kang & Kaplan, 2019).

Conclusion

The mental make-up of men and women is more similar than different (Hyde, 2005, 2014). Despite these similarities, the outcomes and experiences of men and women in science, technology, engineering, and mathematics (STEM) continue to exhibit differences. Gender gaps in STEM are evident in representation (particularly in high-status positions and in subfields of computer sciences and engineering), compensation and, to a lesser extent, grants, publications, and awards. The weight of the evidence no longer supports that these gaps are the result of innate ability differences. Instead, gender gaps in STEM appear, in part, to arise from differences in perceived values and opportunities in environments, as well as pervasive implicit and explicit biases that shape the perceptions of these values and environments. While initial evidence to address disparities is promising, much remains to be understood about the most effective interventions to reduce individual and organizational gender biases. The pursuit of understanding and addressing the causes of gender disparities STEM is crucial to bring our often-biased behaviors and decisions in line with our values of equality and fairness (Charlesworth & Banaji, 2019a). Yet perhaps more importantly, ensuring the full participation of the highest quality candidates (including women) guarantees improvement in the productivity and innovation of STEM discoveries, technologies, and applications that, ultimately, will improve societies.

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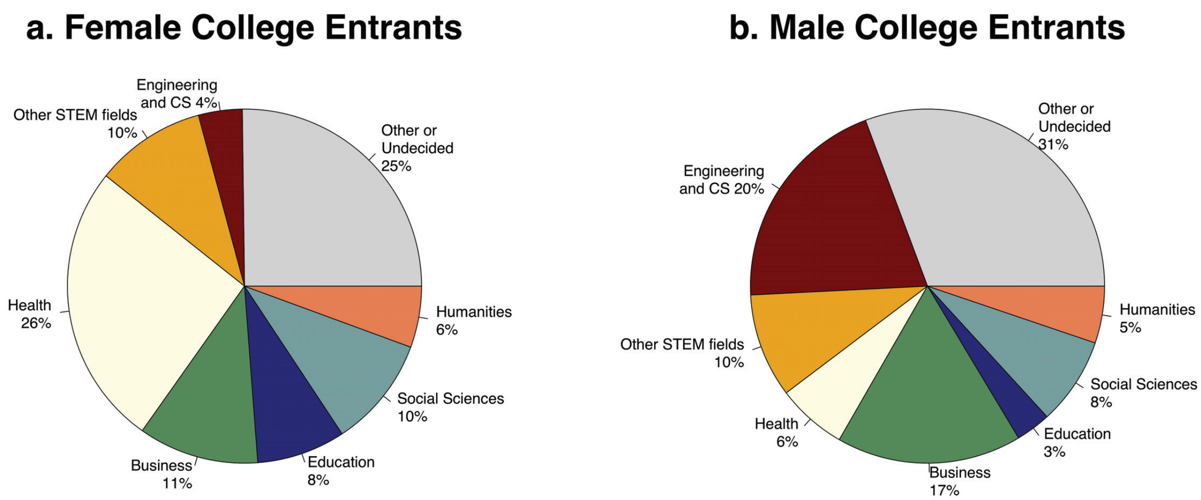
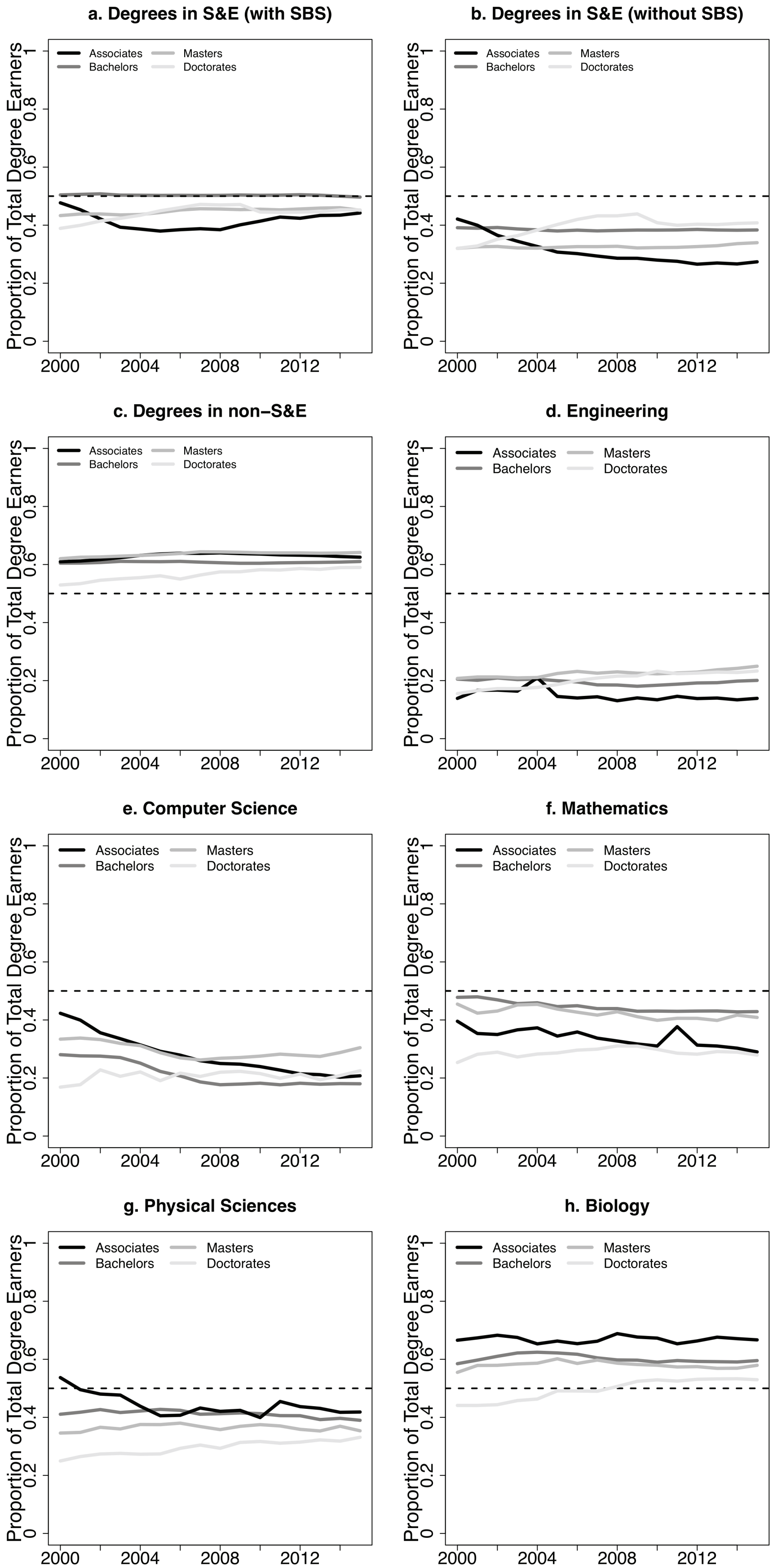

a. Female College Entrants
Engineering and CS 4%
Other STEM fields 10%
Other or Undecided 25%
Health 26%
Humanities 6%
Social Sciences 10%
Business 11%
Education 8%
b. Male College Entrants
Other or Undecided 31%
Engineering and CS 20%
Humanities 5%
Other STEM fields 10%
Social Sciences 8%
Health 6%
Education 3%
Business 17%


a. Degrees in S&E (with SBS)
b. Degrees in S&E (without SBS)
c. Degrees in non−S&E
d. Engineering
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f. Mathematics
g. Physical Sciences
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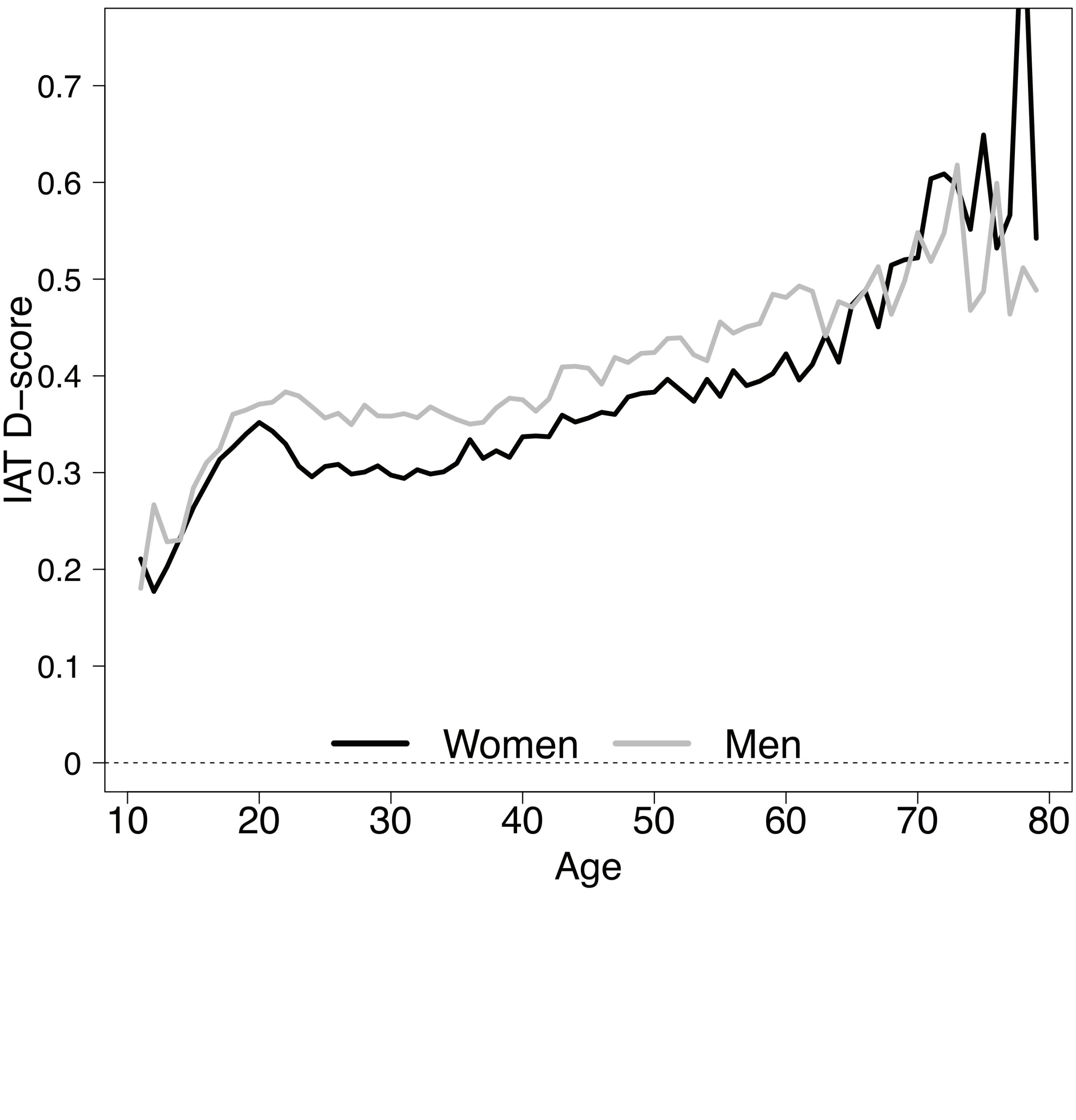
IAT D−score
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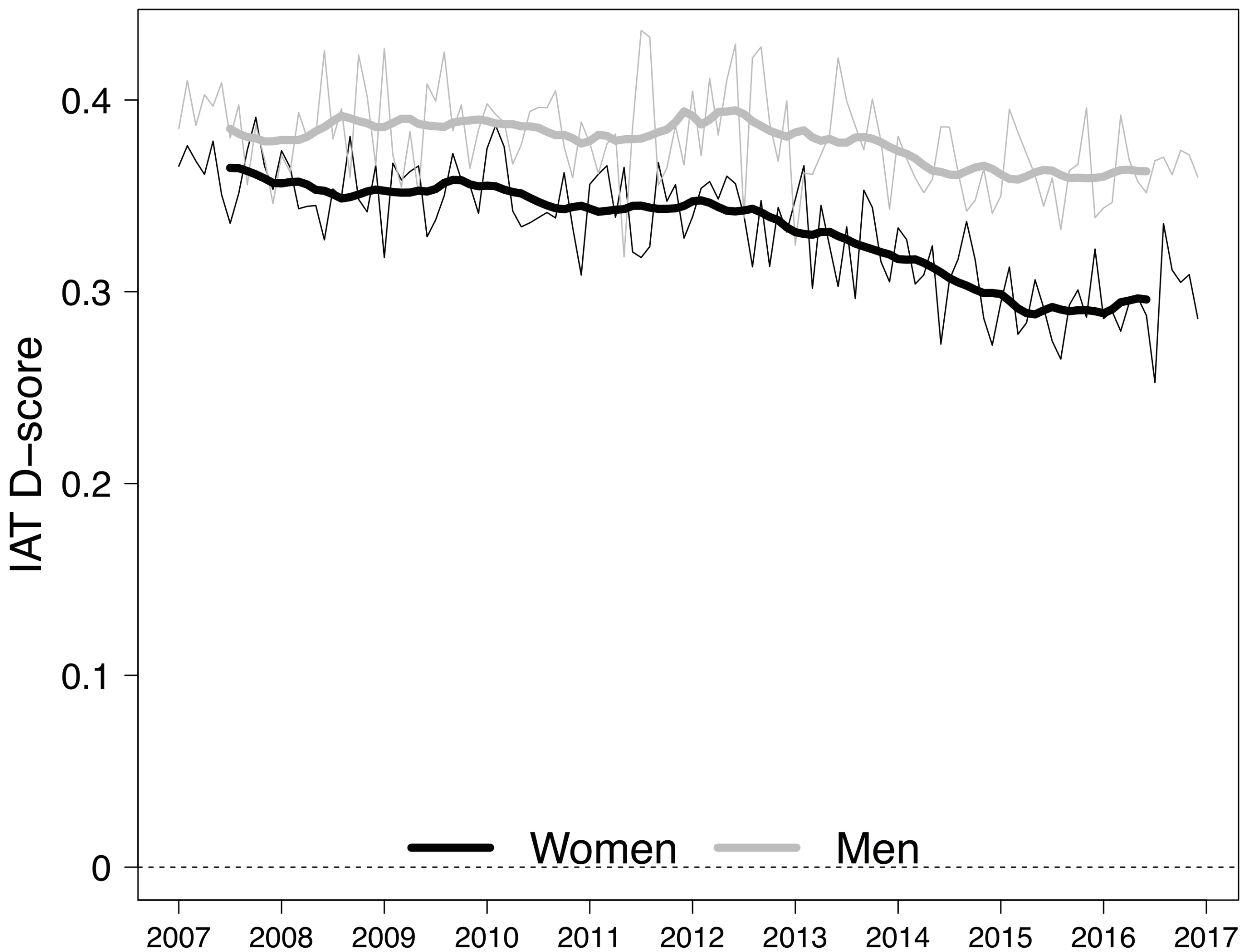
Women
Men



0.4
0.3
0.2
0.1
0
IAT D-score
Women
Men
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

Table 1.
Representation of females across post-secondary education in STEM.

	S&E fields (all)	S&E fields (without SBS)	Non-S&E fields (all)	Engineering	Computer Science	Mathematics	Physical Sciences	Biology
College (Associates)	44%	27%	63%	14%	21%	29%	42%	67%
College (BA)	50%	38%	61%	20%	18%	43%	39%	60%
Graduate School (MA)	45%	34%	64%	25%	30%	41%	35%	58%
Graduate School (PhD)	45%	41%	59%	23%	23%	28%	33%	53%

Note: Data retrieved from the National Science Foundation Science and Engineering Indicators (2018), using the most recent available data from 2015. Within the NSF report, data on associate's degrees are from appendix table 2-18, data on bachelor's degres from appendix table 2-21, data on master's degrees from appendix table 2-27, and data on doctoral degrees from appendix table 2-29. As per NSF, science and engineering S&E fields (all) also include social and behavioral sciences (SBS), in addition to the traditional STEM fields of computer science, mathematics and statistics, physical sciences, and engineering. The traditional STEM fields alone (excluding the SBS fields) are referred to as S&E fields (without SBS) in the table. See https://osf.io/n9jca/ for compiled raw data and code.

Table 2.
Representation of females across career stages in STEM.

	S&E fields (all)	S&E fields (without SBS)	Non-S&E fields (all)	Engineering	Computer Science	Mathematics	Physical Sciences	Biology
Post-doctorates	43%	42%	51%	23%	33%	20%	30%	50%
Junior Faculty	43%	38%	51%	22%	26%	38%	29%	50%
Senior Faculty	31%	27%	39%	14%	19%	21%	20%	39%
Employed Workforce	28%	25%	50%	15%	24%	43%	28%	48%

Note: Data retrieved from the National Science Foundation Science and Engineering Indicators (2018), using the most recent available data from 2015. Within the NSF report, data for academic positions are from appendix tables 5-15, and data for employed workforce from appendix table 3-12. As per NSF, science and engineering (S&E) fields (all) also include social and behavioral sciences, in addition to the more traditional STEM fields of computer science, mathematics and statistics, physical sciences, and engineering. The traditional STEM fields alone (excluding the SBS fields) are referred to as S&E fields (without SBS) in the table. See https://osf.io/n9jca/ for compiled data and code.

Table 3.
Gender pay gap in STEM and non-STEM fields.

	S&E fields (all)	Non-S&E fields (all)	Engineering	Computer Science	Mathematics	Physical Sciences	Biology
Men	95,000	75,000	95,000	100,000	89,000	83,000	68,000
Women	75,000	50,000	88,000	86,000	77,000	60,000	55,000
Gender pay gap	20,000	25,000	7,000	14,000	12,000	23,000	13,000

Note. Median annual salaries (in dollars) of all full-time workers in 2015. Data retrieved from appendix table 3-17 (National Science Foundation, 2018).

Table 4.
Percentage of female authors in STEM and non-STEM peer-reviewed publications, by author status.

	Computer Science	Physics	Mathematics	Chemistry	Biology	Psychology	Education	Health
First Author	17%	17%	19%	35%	43%	50%	61%	50%
Last Author	15%	13%	19%	21%	29%	40%	49%	46%
Any Authorship	16%	17%	18%	30%	37%	48%	55%	49%

Note: Data were most recent available data (2016) retrieved from Holman, Stuart-Fox, and Hauser (2018). Original data was collected from 36 million authors from over 100 countries publishing in over 6000 journals, accessed via PubMed and arXiv databases.