A data-driven approach to reduce gender disparity in invited speaker programs at scientific meetings.

Ann-Maree Vallence[1], PhD

Mark R Hinder[2], PhD

Hakuei Fujiyama[1], PhD

1. School of Psychology and Exercise Science, Murdoch University, Western Australia, Australia
2. School of Medicine, University of Tasmania, Tasmania, Australia

Corresponding Author:

Name: Ann-Maree Vallence

Address: 90 South Street, Murdoch, Western Australia, Australia, 6150

Email: Ann-Maree.Vallence@murdoch.edu.au

Phone: 0061 08 9360 7464

Abstract

Gender disparity continues to be an issue in STEM, with progress requiring consistent and focused efforts. Here, we present a data-driven approach to promote high quality, gender balanced invited speaker selection for neuroscience conferences. We have targeted invited speaker opportunities because underrepresentation of female speakers at international neuroscience conferences remains a major problem, and such opportunities are critical for career development. First, we audited the top ten neuroscience journals (indexed by SCImago Journal and Country Rank; SJR), identifying (1) highly cited papers, (2) gender of first and last authors, and (3) field-weighted citation impact and total publications of first and last authors. Second, we used these data to establish a database of high quality scientists that could be used to select speakers for conferences. We found that research quality (as indexed by field-weighted citation impact and total publications) of authors of highly cited publications in the top 10 neuroscience journals did not differ significantly for females and males. The comparison between the gender base rate in neuroscience and authors publishing highly cited papers in high-quality neuroscience journals shows that female representation, particularly at last author level, is less than the estimated base rate for neuroscience. In summary, we present a data-driven approach to invited speaker selection that would facilitate gender balanced conference programs while maintaining the highest of scientific standards. This approach minimizes the influence of implicit gender bias in speaker selection decisions by using scientific quality metrics that STEM researchers are familiar with, and indeed use to evaluate their own performance. Having an immediate effect on reducing gender disparity in conference programs, our approach would generate a positive spiral for more long-term reduction of gender disparity in STEM.

Significance Statement

Gender disparity is a persistent issue in STEM. We present a data-driven approach to invited speaker selection, based on scientific quality metrics that researchers use to evaluate their own and their peers' performance. We targeted invited speaker opportunities because underrepresentation of female speakers at international conferences remains a major problem, and such opportunities are critical for career development. Research quality of authors of highly cited publications in top neuroscience journals did not differ between females and males. This approach minimizes implicit gender bias in speaker selection, which will immediately reduce gender disparity in conference programs, as well as generate a positive spiral for more long-term reduction of gender disparity in STEM.

Introduction

Gender disparity in academia has been acknowledged for some time. In neuroscience, females represent approximately half of PhD graduates but only 25 - 30% of tenure-track faculty in the US[1,2]. Although many have called for potential solutions to the problem, the disparity persists and progress towards gender balance is slow [3,4].

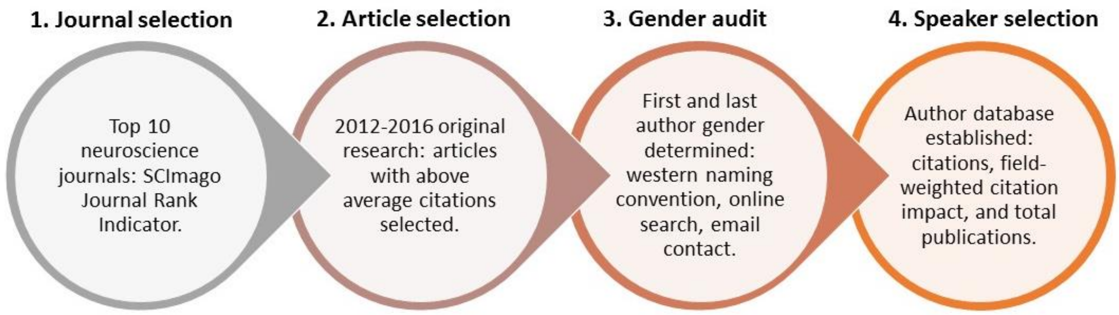
The persistence of gender disparity in neuroscience is likely due, at least in part, to implicit bias[5]: the covert attitudes that influence our understanding, actions, and decisions in an unconscious manner. Evidence suggests that implicit gender bias in science negatively affects outcomes for females in terms of hiring, promotion, funding, and invitations for conference presentations and editorial roles[6-12]. For example, in a randomized double-blind study in which laboratory manager applications were randomly allocated male or female names, faculty at research intensive universities rated male applicants as more competent and offered a higher starting salary than the identical applicant with a female name[6]. It is important to note, however, that within this growing literature investigating gender bias in STEM, some studies show a bias against female scientists[6-12] whilst other studies suggest little bias or, more recently, affirmative treatment of female scientists[13-20].

The negative effects of implicit gender bias can be overcome by either reducing the bias itself, or implementing protocols that minimize the influence of the bias. Here we have developed an approach to *minimize* the influence of bias in the process of selecting invited speakers. To this end, we present a data-driven approach to promote high quality, gender-balanced invited speaker selection for neuroscience conferences. We have targeted invited speaker opportunities because underrepresentation of female speakers at international neuroscience conferences remains a major problem[2], and such opportunities are critical for career development. Whilst there have been some recent suggestions for ensuring gender balance in invited speaker programs (including guidelines for selection[21] and diversity policies[22]), the selection of invited speakers remains largely subjective, leaving it open to negative effects of implicit gender bias.

We developed a two-step approach to minimize the influence of implicit gender bias in invited speaker selection. First, we audited the top ten neuroscience journals (indexed by SCImago Journal and Country Rank; SJR), identifying (1) highly cited papers, (2) gender of first and last authors, and (3) field-weighted citation impact and total publications of first and last authors. Second, we used these data to establish a database of high quality scientists (irrespective of their gender) that could be used to select speakers for conferences. If the quality of scientists on this database is comparable across gender, this approach enables gender balance in invitations that is based on established metrics of quality frequently used by researchers, hiring committees, and funding bodies, thereby minimizing the influence of implicit gender bias on selection decisions. Notably, this approach can have an immediate effect to improve the underrepresentation of female invited speakers at neuroscience conferences, and will likely have a medium- to long-term effect to improve the progression of female scientists to senior levels within STEM.

Method

The study was approved by the Murdoch University Human Research Ethics Committee (2017/206). Figure 1 shows the study procedure. The journal ranking data and citation reports were extracted on the November 26, 2017.



Top 10 journals	SJR	Total articles	Articles audited
Nature Neuroscience	14.1	998	331
Neuron	11.1	1,583	563
The EMBO Journal	6.6	1,006	366
Acta Neuropathologica	6.5	452	154
Biological Psychiatry	6.0	918	341
eLIFE	5.9	2,787	857
Annals of Neurology	5.3	847	280
PLoS Biology	4.8	950	346
Journal of Neuroscience	4.7	7,264	2,618
The Lancet Psychiatry	4.6	146	56
		Total	5,912

Figure 1. Selection procedure for creating a database for speaker selection.

Journal Selection. Neuroscience journals were ranked using the SJR indicator system and Web of Science. The top ten journals comprising ≥50% original research articles were selected for auditing (see Figure 1). (Note: *Molecular Psychiatry* was excluded because more than 60% of publications reported authors' initials only).

Article Selection. Total citations and average citations per year were calculated for each original research article in the selected journals (Citations from 2012-2016 for all journals except *Lancet Psychiatry*, for which citation data were only available from 2014-2016) Articles were selected for the author gender audit if their total citation count was greater than the average total citations for the journal in which the article was published.

Gender identification. The gender of first and last authors of the selected articles was determined to be male, female, or unknown (last author was selected because it typically represents the senior author in neuroscience). Gender determination (using western naming convention) was completed independently by two investigators, and then cross-referenced. If gender could not be determined using this method, or the name was indeterminate or androgynous, an electronic search was conducted using institutional and academic networking websites: gender was determined if the online resources included the author's name, photo (with clear gender identification) and either a reference to the article or the author's affiliation (listed in the article). If gender of first or senior authors could not be determined using either of these methods (6.9%), the corresponding author was emailed to request gender identity information (email response rate: 20%). (In total, the gender of 163 author could not be determined.)

Database for speaker selection. The weighted total citations (2012-2016) were obtained by dividing the total citation counts for each paper by the number of years since its publication. The weighted total citations were then used to rank all articles; the first and last authors of the top 100 ranked articles were included on our 'potential speakers' lists. The field-weighted citation impact (FWCI) and their total number of career publications were obtained for these authors, and the rank order of the lists was then adjusted based on FWCI. (Note: if an author did not have an identifiable FWCI using SciVal they were not included in the database.)

Results

The lists of top 100 first and senior authors based on weighted total citations and subsequently re-ranked based on FWCI showed that 32% of first authors and 21% of last authors were female (supplementary material: Table 1 and Table 2). Figure 2 shows the gender breakdown of authors in the top 100 list for FWCI and total publications. FWCI did not differ between males and females for either first or last authors (p>0.49, Cohen's d<0.15, Bayes Factor, BF_{10}<0.29), indicating no difference in the impact of research between males and females irrespective of career stage. All of the data are available online (see supplementary material 'speaker database').

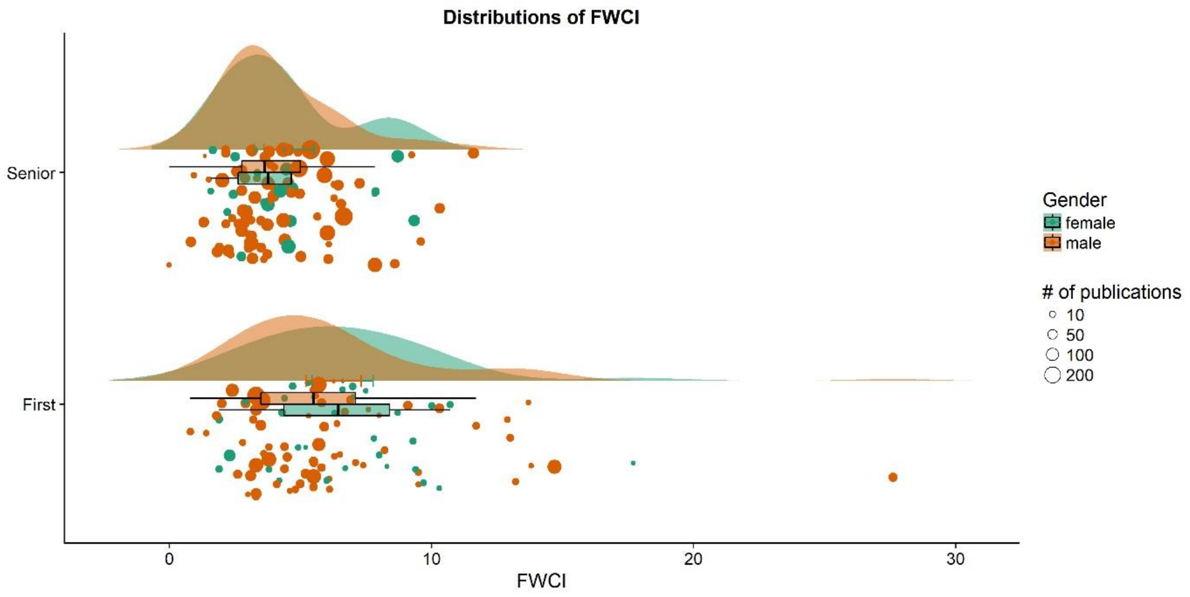


Figure 2. Raincloud plots of field weighted citation impact for female and male first (lower plot) and senior (upper plot) authors in the top 100 list; each circle represents one author, with the size of the circle reflecting the total number of publications (see legend).

The percentage of female first authors from our database (32%) was significantly less than the base rate of female trainees within neuroscience (49%), as determined by biaswatchneuro based on ~20,000 attendees at the Society for Neuroscience conference in 2017 (https://biaswatchneuro.com/base-rates/neuroscience-base-rates/; p <.001, Cohen's w= 0.32); however, the associated Baye's Factor (BF_{10}=2.39) suggests that the empirical data do not provide strong evidence to distinguish the observed percentage from the base rate. In contrast, the percentage of female last authors from our database (21%) was significantly less than the base rate of female faculty within neuroscience (39%), as determined by biaswatchneuro (https://biaswatchneuro.com/base-rates/neuroscience-base-rates/; p <.001, Cohen's w= 0.35, BF_{10}=6.27), suggesting that the observed female representation is less than the estimated base rate in the field of neuroscience.

Figure 3 shows the percentage of female invited speakers across the 387 neuroscience conferences from 2014-2019 that are listed on www.biaswatchneuro.com. The mean percentage of female invited speakers across these conferences was 27%: this percentage of female invited speakers differs substantially from the overall base rate of 45% females in neuroscience (averaged across trainees and faculty from www.biaswatchneuro.com; p<0.001, Cohen's w=4.26, Bayes Factor, BF_{10}=4.05) but does not differ significantly from the observed percentage of female first or last authors as determined from our audit (both p>0.16, both Cohen's w <0.14, both Bayes Factor, BF_{10}<0.34). It is important to note (and indeed it is clear from Fig. 3) that whilst some neuroscience conferences are attaining, or exceeding, the gender base rate of 45% female invited speakers, more than 75% of conferences have less than 40% females in their invited speaker programs. That is to say, more than 75% of conferences are not attaining the gender base rate of females in neuroscience in their invited speaker programs.

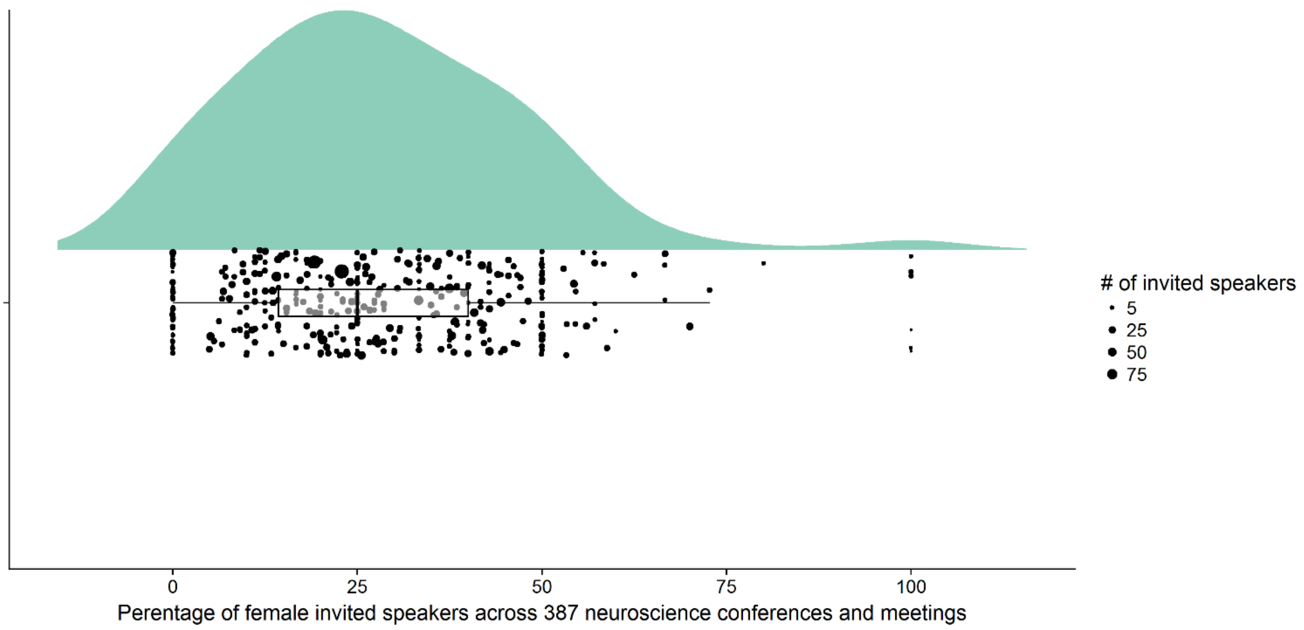


Figure 3. Raincloud plot of the percentage of female invited speakers across the 387 neuroscience conferences from 2014-2019 that are listed on www.biaswatchneuro.com; each circle represents one conference, with the size of the circle reflecting the total number of invited speakers at that conference (see legend).

Discussion

The data driven approach presented here enables speaker selection based on scientific impact, thereby minimizing the influence of implicit bias. Notably, this approach can ensure gender balance, given that the current results show that scientific impact does not differ between males and females in the potential speaker database.

Implicit gender bias is widespread and is proving challenging to overcome, and gender bias in STEM is no exception. Indeed, in a series of randomized, double-blind experiments, males and females evaluated the quality of scientific journal abstracts reporting gender bias in a STEM context: males evaluated abstracts less favorably than females, with male STEM faculty evaluating abstracts less favorably than female STEM faculty and male and female members of the general community[23]. If evidence demonstrating gender bias in STEM is not convincing to a subgroup in STEM who serve as panel members that make decisions regarding hiring, promotion, speaking invitations, and editorial invitations, we have to develop new approaches to negate, or at least minimize, the effects of implicit gender bias. Our approach purposefully includes established metrics of quality that are frequently used by researchers, hiring committees, and funding bodies. The benefits of this approach are twofold. First, it provides a data driven method for selecting invited speakers (both senior researchers as well as early career researchers), which can have an immediate effect on reducing gender disparity at scientific conferences. Second, establishing a database of high quality researchers based on these metrics provides convincing evidence of parity in scientific quality between males and females at the highest level. These benefits should, in turn, lead to a positive spiral in which invited speaking opportunities for females facilitate career development through recognition of high-quality research, providing greater opportunity for collaborative outreach, which will increase likelihood of academic promotion and female leadership within STEM, as well as providing an environment in which implicit bias should become less pervasive. The existence of equity and diversity policies in a growing number of scientific societies provides evidence of a willingness to engage in protocols that ensure more equitable conference programs. Therefore, a data-driven approach to facilitate equitable conference programs is likely to be useful and used by the rapidly growing number of societies that are considering equity and diversity in their decision making for the selection of speakers.

Here we use the broad discipline of neuroscience as an exemplar. The comparison between the gender base rate in neuroscience and authors publishing highly cited papers in high quality neuroscience journals shows that female representation, particularly at senior author level, is less than the estimated base rate for neuroscience. This, together with the data showing that more than 75% of neuroscience conferences are not attaining the gender base rate for female invited speakers, suggests underrepresentation of female scientists is a real problem in the field of neuroscience. It is important to note that we recommend refining the data-driven approach using keywords and/or the selection of specialist journals to ensure that the resultant database of potential speakers is suitable for the target conference or focussed symposia within conferences. Indeed, we have previously shown that the proposed approach would be effective in the sub-discipline of brain stimulation[24]. Establishing the database of potential speakers is largely automated (exportation of publications, citations, and FWCI can be automated, and ranking of authors can be performed with simple code), and the identification of gender could be automated if journals request gender information. Indeed, we call on publishers to collect these data at the proofing stage of publication and make them available post-publication.

Our data-driven approach to speaker selection takes an important step in addressing the complex issue of gender disparity in STEM, and extends beyond tools that are already available by (i) identifying individuals as potential speakers and (ii) overcoming the criticism that selection based on policies and quotas is not merit-based. For example, online calculators can provide estimates of equitable gender representation, and equity and diversity policies can prescribe equitable gender representation, but neither provide any information regarding who to invite to deliver conference or departmental presentations. Furthermore, equity and diversity policies are often subject to the criticism that the selection process is not merit-based. Our approach purposefully includes established metrics of quality that are frequently used by researchers, hiring committees, and funding bodies to overcome this criticism. In addition, the combination of metrics used in our approach provides a list of potential speakers with a recent and relevant high-quality publication, whilst ensuring some stability in terms of career research performance. Some proposed approaches to reduce gender disparity in STEM are data-driven, such as www.biaswatchneuro.com, however these approaches use data to increase accountability for gender disparity in conference programs, not to select speakers as per our approach.

Nonetheless, it is important to acknowledge some limitations with the approach. First, achieving gender balance is not equal to achieving diversity and inclusion: our approach should be extended to ensure representation of minority groups. Indeed, our approach could easily be expanded to include information regarding geographical location, ethnicity, and career stage, which would provide an opportunity to reduce the underrepresentation of minority groups in STEM. Second, our approach relies on the citations of publications in high impact journals. Evidence suggests that female scientists submit fewer manuscripts than male scientists to high quality journals, have fewer manuscripts accepted for publication in high quality journals, and that publications with a female senior author are cited less than publications with a male senior author[8,25,26]. Therefore, although our approach is data-driven, the data themselves are likely to be affected by implicit gender bias that negatively affects female scientists [3,4]: our approach should be continually refined to include the most reliable and well-accepted quality metrics for STEM researchers. We have made the data from this study available online, and we recommend that program committees use these data, as well as continue to collect data, to reduce the underrepresentation of women in speaking programs at conferences. In light of the strengths and limitations of our approach, we argue strongly that a combination of approaches will be most effective at reducing the persistent gender disparity and preventing the emergence of gender bias in STEM, as well as increasing diversity in STEM more generally.

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Supplementary material
Table 1
Top 100 **first** authors based on weighted total citation

Author	Gender	Journal	Year	wTC	TC	FWCI
Iossifov, Ivan	male	Neuron	2016	465.0	465	9.5
Giraud, Anne-Lise	female	Nature Neuroscience	2016	305.0	305	1.9
Jinek, Martin	male	eLife	2013	127.3	509	11.7
Schafer, Dorothy P.	female	Neuron	2013	123.3	493	8.0
Akerboom, Jasper	male	Journal of Neuroscience	2014	119.0	357	6.5
Donnelly, Christopher J.	male	Neuron	2015	109.0	218	7.1
Baliki, Marwan N.	male	Nature Neuroscience	2015	97.5	195	4.4
Lehmann, Sabrina M.	female	Nature Neuroscience	2015	97.0	194	5.2
Butovsky, Oleg	male	Nature Neuroscience	2014	93.3	280	13.2
Bakker, Arnold	male	Neuron	2015	91.0	182	3.1
Klengel, Torsten	male	Nature Neuroscience	2013	90.5	362	5.8
Hickman, Suzanne E.	female	Nature Neuroscience	2015	89.0	178	6.3
Watabe-Uchida, Mitsuko	female	Neuron	2014	88.0	264	6.6
Kierdorf, Katrin	female	Nature Neuroscience	2014	81.7	245	9.3
Montine, Thomas J.	male	Acta Neuropathologica	2012	81.6	408	14.7
Zhang, Ye; Chen	unkown	Journal of Neuroscience	2013	78.8	315	0.1
Taylor, Michael D.	male	Acta Neuropathologica	2012	77.8	389	3.3
Madisen, Linda	female	Nature Neuroscience	2013	74.3	297	9.4
Crary, John F.	male	Acta Neuropathologica	2015	70.0	140	8.2
Hipp, Joerg F.	male	Nature Neuroscience	2014	64.7	194	2.8
Dulvy, Nicholas K.	male	eLife	2014	64.3	193	5.9
Usoskin, Dmitry	male	Nature Neuroscience	2015	63.0	126	13.7
Bazzini, Ariel A.	male	EMBO Journal	2015	63.0	126	6.1
Settembre, Carmine	male	EMBO Journal	2012	63.0	315	4.4
Griciuc, Ana	female	Neuron	2014	62.3	187	7.5
Dannlowski, Udo	male	Biological Psychiatry	2013	62.3	249	2.9
Kool, Marcel	male	Acta Neuropathologica	2013	62.0	248	5.7
Dias, Brian G.	male	Nature Neuroscience	2013	61.0	244	4.8
Montagne, Axel	male	Neuron	2015	60.0	120	3.3
Kravitz, Alexxai V.	male	Nature Neuroscience	2013	59.8	239	3.2
Zamanian, Jennifer L.	female	Journal of Neuroscience	2012	58.0	290	17.7
van Zessen, Ruud	male	Neuron	2014	56.7	170	5.3
Ash, Peter E. A.	male	Neuron	2012	56.2	281	6.3
Leech, Robert	male	Journal of Neuroscience	2014	55.0	165	3.3
Scher, Jose U.	male	eLife	2013	54.0	216	6.7
Miron, Veronique E.	female	Nature Neuroscience	2012	53.8	269	5.3
MacLeod, David A.	male	Neuron	2014	53.7	161	1.4
Yu, Timothy W.	male	Neuron	2014	53.0	159	6.9
Cajigas, Ivan J.	male	Neuron	2014	53.0	159	3.0
Grienberger, Christine	female	Neuron	2013	52.3	209	2.9
Plavina, Tatiana	female	Annals of Neurology	2015	52.0	104	10.7
Bastos, Andre Moraes	male	Neuron	2015	52.0	104	6.1

Lagier-Tourenne, Clotilde	female	Nature Neuroscience	2013	51.0	204	7.0
Sauvageau, Martin	male	eLife	2013	49.8	199	12.9
Iba, Michiyo	unkown	Journal of Neuroscience	2014	49.0	147	6.5
Kraemer, Moritz U. G.	male	eLife	2015	48.5	97	13.0
Brettschneider, Johannes	male	Annals of Neurology	2014	48.0	144	5.5
Ke, Meng-Tsen	female	Nature Neuroscience	2013	47.3	189	5.5
Gapp, Katharina	female	Nature Neuroscience	2013	47.0	188	6.0
Knobloch, H. Sophie	female	Neuron	2012	46.8	234	7.0
Agarwal, Vikram	male	eLife	2013	46.8	187	0.8
Freischmidt, Axel	male	Nature Neuroscience	2015	45.5	91	3.6
Kordasiewicz, Holly B.	female	Neuron	2013	44.8	179	4.9
Balbas, Minna D.	female	eLife	2014	44.7	134	10.3
Jack, Clifford R., Jr.	male	Annals of Neurology	2012	44.6	223	3.5
Young, Kaylene M.	female	Neuron	2013	44.0	176	1.9
Atallah, Bassam V.	male	Neuron	2013	43.5	174	4.6
Garg, Abhishek D.	male	EMBO Journal	2013	43.0	172	5.2
Cole, Michael W.	male	Nature Neuroscience	2012	41.0	205	5.5
Steentoft, Catharina	female	EMBO Journal	2012	41.0	205	4.3
Pigott, David M.	male	eLife	2014	40.0	120	27.6
Bosman, Conrado A.	male	Neuron	2012	40.0	200	3.8
Zarate, Carlos A., Jr.	male	Biological Psychiatry	2012	39.0	195	3.3
Threlfell, Sarah	female	Neuron	2012	37.4	187	3.3
Mendell, Jerry R.	male	Annals of Neurology	2013	37.3	149	3.5
Orenstein, Samantha J.	female	Nature Neuroscience	2013	37.0	148	8.3
Wheaton, William W.	male	eLife	2014	36.0	108	13.8
Guo, Junjie U.	male	Nature Neuroscience	2013	36.0	144	6.4
Dong-Anh Khuong-Quang	female	Acta Neuropathologica	2012	35.6	178	10.0
Zaki, Jamil	male	Nature Neuroscience	2012	35.0	175	1.8
Noble, Kimberly G.	female	Nature Neuroscience	2015	34.5	69	4.7
Kijas, James W.	male	PLoS Biology	2012	34.0	170	2.6
Tan, Kelly R.	female	Neuron	2012	32.4	162	4.2
Faber, Catharina G.	female	Annals of Neurology	2012	32.2	161	2.3
Deplus, Rachel	female	EMBO Journal	2012	32.0	160	3.8
Mouillot, David	male	PLoS Biology	2013	32.0	128	3.3
Hughes, Ethan G.	male	Nature Neuroscience	2013	31.5	126	7.6
McLelland, Gian-Luca	male	EMBO Journal	2013	30.3	121	9.5
Kessler, Ronald C.	male	Biological Psychiatry	2012	30.2	151	3.8
Rodgers, Ali B.	unkown	Journal of Neuroscience	2012	29.4	147	7.3
Ziv, Yaniv	male	Nature Neuroscience	2012	29.4	147	4.5
Elmore, Monica R. P.	female	Neuron	2012	29.4	147	4.4
De Jager, Philip L.	male	Nature Neuroscience	2013	29.0	116	5.5
Recasens, Ariadna	female	Annals of Neurology	2013	28.8	115	6.7
Musiek, Erik S.	male	Nature Neuroscience	2014	27.3	82	5.8
Erny, Daniel	male	Nature Neuroscience	2013	27.0	108	7.4
Paz, Jeanne T.	female	Nature Neuroscience	2012	25.4	127	7.8
Cole, Michael W.	male	Neuron	2012	24.6	123	5.5

O'Dushlaine, Colm	male	Nature Neuroscience	2012	20.4	102	10.3
Sojka, Dorothy K.	female	eLife	2012	20.4	102	9.7
Scheres, Sjors H. W.	male	eLife	2012	20.2	101	9.1
Alami, Nael H.	male	Neuron	2012	19.6	98	8.0
Deisseroth, Karl	male	Nature Neuroscience	2013	19.3	77	5.7
Cannon, Tyrone D.	male	Biological Psychiatry	2013	16.5	66	2.4
Sorge, Robert E.	male	Nature Neuroscience	2012	16.2	81	4.1
Herrup, Karl	male	Nature Neuroscience	2012	14.0	70	2.0
Reuss, David E.	male	Acta Neuropathologica	2012	13.8	69	5.0
Khodagholy, Dion	male	Nature Neuroscience	2012	13.0	65	5.5
Tasic, Bosiljka	female	Nature Neuroscience	2013	10.0	40	8.7
Hamid, Arif A.	male	Nature Neuroscience	2012	6.6	33	5.6

FWCI: field-weighted citation impact ; TC: total citation; wTC; weighted total citation

Supplementary material
Table 2
Top 100 **first** authors based on weighted total citation

Author	**Gender**	**Journal**	**Year**	**wTC**	**TC**	**FWCI**
Doudna, Jennifer	female	eLife	2013	127.3	509	9.06
Wu, Jia Qian	female	Journal of Neuroscience	2014	105.0	315	9.08
Stevens, Beth	female	NEURON	2012	98.6	493	11.31
Bartel, David P.	female	eLife	2015	93.5	187	9.68
Weiner, Howard L.	male	Nature Neuroscience	2014	93.3	280	4.66
Wigler, Michael	male	NEURON	2012	93.0	465	2.98
Binder, Elisabeth B.	male	Nature Neuroscience	2013	90.5	362	4.26
Hyman, Bradley T.	female	NEURON	2012	89.2	446	4.39
Hyman, Bradley T.	male	Acta Neuropathologica	2012	81.6	408	4.39
Pfister, Stefan M.	male	Acta Neuropathologica	2012	77.8	389	5.97
Looger, Loren L.	male	Journal of Neuroscience	2012	71.4	357	5.52
Petrucelli, Leonard	male	NEURON	2013	70.3	281	5.74
Ffrench-Constant, Charles	male	Nature Neuroscience	2013	67.3	269	3.57
White, William T.	male	eLife	2014	64.3	193	1.49
Ballabio, Andrea	male	EMBO Journal	2012	63.0	315	4.07
Ernfors, Patrik	male	Nature Neuroscience	2015	63.0	126	3.77
Mansuy, Isabelle M.	male	Nature Neuroscience	2014	62.7	188	2.42
Prinz, Marco	female	Nature Neuroscience	2013	61.3	245	3.38
Poeppel, David	male	Nature Neuroscience	2012	61.0	305	2.63
Zlokovic, Berislav V.	male	NEURON	2015	60.0	120	5.48
Zeng, Hongkui	male	Nature Neuroscience	2012	59.4	297	5.4
Barres, Ben A.	female	Journal of Neuroscience	2012	58.0	290	8.28
Scanziani, Massimo	male	Nature Neuroscience	2013	56.8	227	7.02
Rothstein, Jeffrey D.	male	NEURON	2013	54.5	218	5.6
Littman, Dan R.	male	eLife	2013	54.0	216	6.93
Prinz, Marco	male	Nature Neuroscience	2015	54.0	108	3.38
Gross, Cornelius T.	male	Nature Neuroscience	2014	51.7	155	2.38
Braver, Todd S.	male	Nature Neuroscience	2013	51.3	205	4.63
Clausen, Henrik	male	EMBO Journal	2013	51.3	205	2.51
Breen, Gerome	male	Nature Neuroscience	2015	51.0	102	4.58
Kugel, Harald	male	Biological Psychiatry	2012	49.8	249	2.33
Rinn, John L.	male	eLife	2013	49.8	199	12.79
Pfister, Stefan M.	male	Acta Neuropathologica	2012	49.6	248	5.97
Hay, Simon I.	male	eLife	2015	48.5	97	29.39
Scheres, Sjors H. W.	male	eLife	2013	48.3	193	9.11
Kreitzer, Anatol C.	male	Nature Neuroscience	2012	47.8	239	5.76
Nelson, Peter T.	male	Acta Neuropathologica	2014	46.7	140	5.2
Simcoe, Timothy S.	male	PLoS Biology	2015	46.5	93	6.6
Weishaupt, Jochen H.	male	Nature Neuroscience	2015	45.5	91	3.07
Petersen, Ronald C.	male	Annals of NeurologyS	2012	44.6	223	3.88
Janak, Patricia H.	male	Nature Neuroscience	2013	44.5	178	3.09
Richardson, William D.	female	NEURON	2013	44.0	176	4.32

Diamond, Marc I.	male	NEURON	2014	43.3	130	4.9
Giraldez, Antonio J.	male	EMBO Journal	2014	42.0	126	6
Konnerth, Arthur	male	NEURON	2012	41.8	209	2.24
Clevers, Hans	male	EMBO Journal	2012	41.2	206	6.43
Petersen, Steven E.	male	NEURON	2014	41.0	123	7.37
Holtzman, David M.	male	Nature Neuroscience	2015	41.0	82	5.65
Yeo, Gene W.	male	Nature Neuroscience	2012	40.8	204	4.3
Mogil, Jeffrey S.	male	Nature Neuroscience	2015	40.5	81	3.39
Abeliovich, Asa	male	NEURON	2013	40.3	161	4.45
Hay, Simon I.	male	eLife	2014	40.0	120	30.23
Zeng, Hongkui	male	Nature Neuroscience	2016	40.0	40	5.4
Fuks, Francois	male	EMBO Journal	2013	40.0	160	3.14
Tsien, Roger Y.	male	Nature Neuroscience	2013	40.0	160	3.09
Walsh, Christopher A.	female	NEURON	2013	39.8	159	4.8
Lindemann, Lothar	male	NEURON	2012	39.0	195	3.71
Luckenbaugh, David A.	male	Biological Psychiatry	2012	39.0	195	2.77
Livesey, Frederick J.	female	Nature Neuroscience	2012	38.8	194	4.07
Lehnardt, Seija	male	Nature Neuroscience	2012	38.8	194	2.28
Engel, Andreas K.	male	Nature Neuroscience	2012	38.8	194	1.65
Sowell, Elizabeth R.	male	Nature Neuroscience	2015	38.5	77	2.6
Adams, Ortwin	female	Annals of NeurologyS	2014	38.3	115	1.41
Cragg, Stephanie J.	male	NEURON	2012	37.4	187	2.51
Kaye, Edward M.	female	Annals of NeurologyS	2013	37.3	149	7.72
Sperling, Reisa	female	Annals of NeurologyS	2016	37.0	37	5.19
Cuervo, Ana Maria	male	Nature Neuroscience	2013	37.0	148	3.57
Lee, Virginia M-Y	unknown	Journal of Neuroscience	2013	36.8	147	4.69
Schnitzer, Mark J.	female	Nature Neuroscience	2013	36.8	147	4.29
Bale, Tracy L.	male	Journal of Neuroscience	2013	36.8	147	3.35
Seeley, William W.	unknown	NEURON	2012	36.6	183	4.27
Gallagher, Michela	male	NEURON	2012	36.4	182	1.76
Doudna, Jennifer A.	female	eLife	2014	36.3	109	9.1
Trojanowski, John Q.	female	Annals of NeurologyS	2013	36.0	144	5.16
Chandel, Navdeep S.	male	eLife	2014	36.0	108	4.65
Cleveland, Don W.	male	NEURON	2012	35.8	179	3.92
Hawkins, Cynthia	male	Acta Neuropathologica	2012	35.6	178	3.63
Birbaumer, Niels	female	Annals of NeurologyS	2013	35.5	142	1.9
Gold, Joshua I.	male	NEURON	2016	35.0	35	3.3
Ochsner, Kevin	male	Nature Neuroscience	2012	35.0	175	3.28
Vanderhaeghen, Pierre	male	NEURON	2013	35.0	140	2.81
Scanziani, Massimo	male	NEURON	2012	34.8	174	7.02
Akassoglou, Katerina	male	Annals of NeurologyS	2014	34.7	104	3.43
Sulzer, David	male	NEURON	2014	34.7	104	2.74
von Deimling, Andreas	male	Acta Neuropathologica	2015	34.5	69	5.54
Gitler, Aaron D.	female	Nature Neuroscience	2015	34.5	69	4.39
Strittmatter, Stephen M.	female	Nature Neuroscience	2012	34.2	171	2.85
Rubin, Gerald M.	female	eLife	2014	34.0	102	5.75

Rubin, Gerald M.	male	eLife	2014	34.0	102	5.75
Stuber, Garret D.	male	NEURON	2012	34.0	170	4.53
Yokoyama, Wayne M.	male	eLife	2014	34.0	102	4.26
Vosshall, Leslie B.	male	NEURON	2014	34.0	102	4.06
Nowak, Martin A.	female	eLife	2013	34.0	136	2.96
Dalrymple, Brian	male	PLoS Biology	2012	34.0	170	2.24
Church, George M.	male	eLife	2014	33.7	101	6.89
Khakh, Baljit S.	male	Nature Neuroscience	2014	33.7	101	6.06
Lin, Michael Z.	male	Nature Neuroscience	2014	33.7	101	4.19
Sawyers, Charles L.	male	eLife	2013	33.5	134	8.27
Rudy, Bernardo	male	Nature Neuroscience	2013	33.5	134	4.36
Apkarian, A. Vania	unknown	Nature Neuroscience	2012	0.7	3.57	3.55

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