Twitter as a community communication tool for international neuroscience conferences

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Scientific conferences increasingly include online aspects. Some are moving to be entirely virtual while others are adopting hybrid models in which there are both in-person and virtual elements. This development of opportunities for people to attend conferences virtually has the potential to both reduce their environmental impact and to make access to them more equitable. An issue with virtual conference participation that has been raised, however, is that there is a reduction in informal communication between attendees. This is an important deficit as such informal contacts play a significant role in both knowledge transmission and professional network development. One forum where some informal communication around conferences does occur is Twitter, with this being encouraged by some conferences. It is not clear, though, to what extent the informal networks built around this service help reduce the problems of unequal access see with in-person conferences. Focusing on geographical equity, we looked at Twitter usage surrounding four international conferences between 2010 and 2021. It was found that engagement with conference hashtags increased steadily over time, peaking in 2019. Users represented 9% of conference attendees and were primarily located in Europe and North America, communicating primarily in English (97% of tweets). Hub nodes within the interaction network were also primarily located in these regions. East Asia had fewer users than would be expected based on neuroscience publication numbers from that region. What users there were in East Asia were engaged with less than were users in other regions. It was found that the overall interaction network showed a rich-club structure, where users with more connections tend to interact more with others with similar connections. Finally, it was found that users in Europe and North America tend to communicate with other users in their own regions whereas users in the rest of the world direct their interactions out of their region. These results suggest that although conference-related Twitter use has been successful to some degree in opening up access, there are some notable limitations in its usage that may mirror aspects of inequality inherent to in-person conferences. How to build equitable informal communication networks around virtual conferences remains a challenging question that requires further discussion.

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Introduction

Conferences play an important role in the scientific process. As well as providing a venue for information dissemination, they also form part of the social structures that underlie the production of scientific knowledge and academic researchers' career development (1, 2). These outcomes are achieved through both the formal aspects of conferences, such as talks and symposia, and through the informal contacts between participants that can occur (3). Historically, such scientific conferences have predominantly been organised as in-person events held at a single location. Problems with this model have, however, become increasingly discussed.

The first such issue is inequality of access to, and representation at, in-person conferences. People from lower-income countries are often excluded due to issues of cost or problems obtaining visas (4, 5). Likewise, early-career researchers and those from smaller institutions can also find themselves unable to afford conference attendance. At the same time, groups such as women, LGBT+ people, and ethnic minorities can be under-represented as speakers at conferences and on organising committees (6, 7). Together, these factors can mean that opportunities to express views and to develop networks can be concentrated around people from particular geographical locations and with similar experiences.

A second issue of traditional conferences is their negative environmental impact, driven primarily by greenhouse gas emissions from air travel (8, 9). The estimated average CO_2e emissions for a person travelling to an international conference are about three tonnes (10). This is equivalent to what a person in a low-income country would produce in a decade and is unsustainable under current conditions if global heating is to remain under 1.5°C (11, 12).

A potential solution for these issues that has been increasingly highlighted is adding more online aspects to conferences. Suggested changes range from making traditional physical conferences hybrid events with simultaneous online components to the creation of conferences that are entirely virtual (13, 14). Experiences from conferences that moved online due to COVID-19 restrictions have provided evidence for the efficacy of these changes, lending support to their wider acceptance. In particular, access for previously under-represented groups was improved for virtual conferences compared to in-person events in previous years (14, 15). At the same time, these virtual events remove the need for air travel and so almost entirely eliminate conference-related carbon pollution (11).

A shift online brings its own issues though (16, 17). In particular, participants of online conferences report that the experience struggles to replicate the informal interactions that occur at in-person conferences (13, 15, 18). These are of key importance as evidence suggests that the development of personal networks that they foster may play a greater role than formal conference presentations in both knowledge transmission and career development (2, 19, 20). Similarly, a range of evidence points to the importance of direct communication for knowledge transmission and for the development of collaborative research .

One service that has been put forward as providing a medium for direct, informal online conference conversations is Twitter. Many conferences promote Twitter use with conference specific hashtags and, in some cases, integrate Twitter messages with conference presentations or discussions (21–23). There is also an existing body of scientists who use Twitter to communicate about their work with other scientists and the wider community (24–26). It must be asked, however, how successful Twitter is in this role in order to build informal scientific networks that are effective and equitable. If a negative aspect of in-person conferences is their exclusivity and perpetuation of existing power-dynamics then it would be important to know to what degree Twitter-based communication reflects or alters those patterns.

To this end, we looked at Twitter use across four international neuroscience conferences. These include two general neuroscience conferences and two neuroimaging specific ones. Engagement with each conference's Twitter hashtag was analysed in terms of user numbers and user interactions. In particular, the distribution of users across different countries was investigated to establish who is contributing to the conversation and whether access to this conversation appears to be geographically equitable. Other forms of equity, such as gender and within-region ethnicity differences, were unfortunately not able to be analysed with the publicly available information used.

Methods

Ethical considerations

The analysis was conducted using information made publicly available by individuals through their Twitter profiles or journal publications. The content of individual tweets was not analysed, with only general properties, such as numbers of tweets or the locations users enter in their profile, being of interest. As the use of Twitter comes with legal jeopardy in some countries, specific location information for users in those places was removed. All usernames were converted to random strings to further protect individual privacy. The study was deemed exempt from review by the Taipei Medical University Institutional Review Board (N202203175).

Conferences

Four international conferences in the brain science domain were included: The Organisation for Human Brain Mapping Annual Meeting (OHBM); The International Society for Magnetic Resonance in Medicine Annual Meeting (ISMRM); The Society For Neuroscience Conference (SfN); and the Federation of European Neuroscience Societies Forum (FENS). OHBM (~2500 attendees) and ISMRM (~5000 attendees; (27)) were included as two specialist conferences directly familiar to the author. SfN (~27,500 attendees; (28)) and FENS (~6500 attendees; (29)) were included as more general brain science conferences that involve a wider range of attendees. Tweets from conferences between 2010 and 2021 were studied. The FENS conference is held biennially in even-numbered years. SfN was cancelled in 2020 and so no data from that year were available. For each conference, the hashtag studied was its acronym plus the year (e.g., #OHBM2020). This format is commonly promoted by conference organisers and has the advantage of being distinct enough to be unlikely to return unrelated tweets. A manual check of tweets was conducted to remove any that were obviously unrelated to the conferences (e.g., discussion of the East Anglian Fens under the FENS conference hashtags).

Tweet information

Individual tweets containing the relevant hashtags were automatically searched for using the *Twint* package (https://github.com/twintproject/twint) running on Python 3.8. Unique usernames for each hashtag were identified and the number of tweets using the relevant hashtag sent by each calculated. The numbers of "likes", "retweets", and replies for each user per hashtag were established. These were then summed to give an overall count of interactions that each user had. The proportion of twitter users for each conference relative to the number of registered attendees was calculated for 2018. This year was chosen as the most recent year where all four conferences were held without COVID-19 related disruption.

The language of each tweet was predicted using the CLD3 model (30) implemented in the *pycld3* package (https://github.com/bsolomon1124/pycld3). Only tweets with six or more words were used, excluding any URLs. Tweets where the classification of the language had a certainty of less than 90% were not included in the estimates. The proportion of tweets that were classified as being in English versus other languages was calculated.

User locations

The geographical location connected to each user was extracted from their profile. This information was not available for all users as adding location information to a profile is optional and not all users include it. Note also that since the information is entered by the user it reflects the location which they wish to share and may not be the location at which they are actually at.

Having automatically extracted tweet locations from the user profiles, these were then manually modified according to the following criteria: 1) Fictional or impossible locations were deleted (e.g., "Narnia"); 2) Overly general locations were deleted (e.g., "Earth"); 3) Specific street addresses were removed (e.g., "No. 80 Street, Glasgow, United Kingdom" changed to "Glasgow, United Kingdom"); 4) Locations in non-Latin script were converted; 5) Flag emojis or nicknames for locations were converted; and 6) City names in countries where Twitter is blocked were removed (e.g., "Xi'an, China" changed to "China"). Where more than location was given, the first was used.

Latitude and longitude for each location was established using the *GeoPy* package (https://geopy.readthedocs.io/en/stable/), interfacing with the Google Maps API. The same API was used to confirm the country in which each user was located. Countries were also split into general geographical regions, such as South East Asia, North America, and Africa (see Table S1 for details; note that there were insufficient tweets from the region to support a more fine-grained division of the African continent).

Publication locations

To investigate whether patterns of tweets could be explained by differences in the number of people in each country doing research related to the conferences, location information from a set of relevant journal articles was collected. The journals looked at were *Journal of Neuroscience*, *European Journal of Neuroscience*, *Frontiers in Neuroscience*, *Frontiers in Human Neuroscience NeuroImage*, *Human Brain Mapping*, and *Magnetic Resonance in Medicine*. These journals are either the journals of the societies that organise the conferences studied or are closely associated with the community attending them. A search on Pubmed (https://pubmed.ncbi.nlm.nih.gov/) was conducted for each journal, limited to publication dates between 2010 and 2020. Pubmed searches were conducted with the *PyMed* package (https://github.com/gijswobben/pymed).

The country of origin for each article was based upon the first affiliation of the senior author where the affiliation of more than one author was listed. Items in each journal that did not have an author attached (e.g., notes from the journal editor, corrigenda) were removed. Similarly, affiliations where the country was not clear were excluded from the analysis. A mean of 3.8% of papers were excluded in this way (range = 0.3-10.9%; Table S2) Countries were assigned to geographical regions in the same manner as Twitter users (Table S1). Eleven countries from which there were Twitter users did not have any publications (15.7%; Table S3).

Interaction networks

Networks of interactions between different users were established based upon to whom a tweet with a conference hashtag was indicated as being a reply to and upon any usernames included in the body of a tweet. The users identified in this way overlap with those directly using the conference hashtags but also includes additional users. Each user was taken as a node and the presence of a reply or mention of a username taken as an edge. Unweighted edges were used so that multiple tweets within a single conversation did not bias any individual user's relative contribution to the network. Networks were built that both included all users and only those users for whom location information was available. Networks were created and analysed using the *NetworkX* package (31).

Degree centrality was calculated for each network node. These were then used to establish the rich-club coefficient at each node centrality (32). The presence of a rich-club organisation was tested through comparison to 500 randomised networks (33). Such an organisation would indicate that nodes with a given degree are more connected to similarly well connected nodes than they are to nodes that are less well connected. A VoteRank algorithm was then applied to identify the 5% most important nodes in the network in terms of influence on information flow across it (34). Both rich-club and high-importance nodes were localised to regions. Finally, whether users were more likely to interact with others inside the same region as them or with users in other regions was quantified as the ratio of intra- to extra-regional edges.

Statistical analysis

The activity of users in terms of the number of tweets sent and number of interactions per tweet were first compared between users who had location information and those who did not to ensure those with information were not unrepresentative of users as a whole. The same metrics from the full dataset were then compared between conferences and across years. These comparisons were made through pseudo-rank Kruskal-Wallis tests (35) followed by Dunn's post-hoc tests with FDR correction for multiple comparisons (using *PyNonpar* and *scikit_posthocs* packages, respectively) The statistical threshold for Kruskal-Wallis tests was $p = 0.05$ and $q = 0.05$ for Dunn's tests.

The influence of geographical location on twitter behaviour and engagement was then tested. Firstly, users numbers in each country were correlated with the number of neuroscience publications from that country. This was done using Spearman's correlation after log-transformation of the user and publication numbers. Countries that had no publications were excluded from this analysis. Next, countries that had unusually low or high users relative to their publication numbers were identified by calculating the Mahalanobis distance of each from the log(user) x log(publication) distribution and identifying distances greater than a threshold of $p = 0.005$ from a χ^2 distribution with two degrees of freedom. Finally, the number of tweets sent by each user and the number of interaction they had per tweet were then compared between the eight different regions (Kruskal-Wallis & Dunn's tests).

In a final step, the user interaction networks were analysed. Median node degree was first compared between the full network and the network for which location information was available to ensure that the latter can be considered representative (Kruskal-Wallis test). Following this, the number of top 5% nodes per region was compared to the number expected given the total number of nodes per region (G-test).

Conference	Total users	Unique users	Tweets	Interactions	Location (%)
FENS	2183	1881	11586	109192	77.9
ISMRM	698	564	2666	22462	75.4
OHBM	3227	2272	16249	186267	77.8
SfN	5880	4705	12356	109462	79.4

Table 1. Summary statistics for each conference.

Results

Conference engagement

A total of 42,857 tweets from 11,988 users were sent using the conference hashtags, producing 427,383 interactions. Of the total number of users, 8,638 were unique (i.e., not counting contributions to more than one conference or year). 6,638 unique users had location information available (76.8%). Numbers for each conference are shown in Table 1. Taking 2018 as an example year, Twitter users represented 9.0% of conference attendees (FENS = 10.5%; ISMRM = 1.2%; OHBM = 19.5%; SfN = 4.7%).

Overall, each user sent a median of one tweet per conference (IQR = 1.0-3.0, range = 1-444) and had a median of five interactions per tweet (IQR = 1.6-12.0, range = 0-2825). Users for whom location information was available sent a mean of 0.06 more tweets ($H_{(1)}$ = 21.77, p = 3.07e-6) but had the same number of interactions per tweet ($H_{(1)}$ = 2.56, p = 0.11). The difference in the number of tweets sent was deemed to have no practical significance and so users with location details were treated as directly comparable to those without.

The number of tweets sent by each user differed between conferences, with users of all conferences but SfN sending a median of two tweets each and SfN users sending one ($H_{(3)}$ = 1017.48, p = 0.0; Figure S1A). The number of interactions per tweet also differed between conferences ($H_{(3)}$ = 412.32, p = 0.0), with OHBM users having the most (M = 7.5, IQR = 3.0-15.0, n = 3227) and ISMRM users the least (M = 3.8, IQR = 1.0-10.0, n = 698; Figure S1B).

Looking at how conference engagement changed over time, the overall number of tweets sent increased each year, from 428 in 2010 to a maximum of 10,179 in 2019 (Figure 1A). A dip in this positive trend occurred in 2020 and 2021. The number of tweets sent per user also generally increased across the time studied ($H_{(11)}$ = 347.37, p = 0.0; Figure 1B), with some fluctuations, as did the number of interactions per tweet ($H_{(11)}$ = 6505.21, p = 0.0; Figure 1C). A drop in both the number of tweets sent per user and in interactions per tweet was seen in 2021. The pattern of increasing engagement followed by a drop-off in 2020 and 2021 was similar for each conference individually, with the exception of FENS where numbers remained high in 2020 (Figure S2).

The language of an average of 76.3% (SD = 9.6%) tweets across conferences and years could be classified with at least 90% accuracy. Of these, a mean of 97.8% (SD = 1.9%) were classified as being in English.

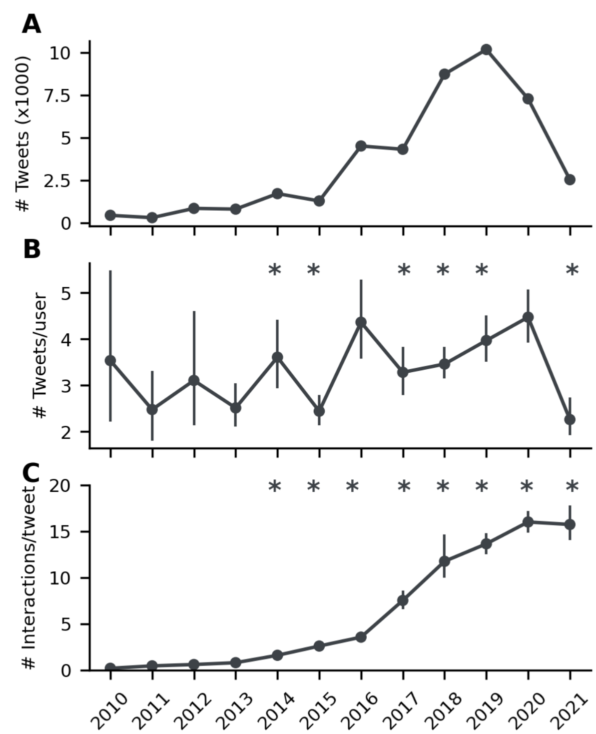

Figure 1. (A) Number of tweets sent per year increases to a maximum in 2019 then falls to a low in 2021. (B) The number of tweets sent per user fluctuates by year, generally increasing to a peak in 2020 and then dropping off. (C) Users have an increasing number of interactions per tweet by year, with a slight reduction in 2021. * indicates a change relative to the prior year (q < 0.05).

User location

The geographical distribution of users is shown in Figure 2A. Users came from 70 different countries and were predominantly located in North America and in Europe (Figure 2B).

User numbers for a country were correlated with its number of neuroscience publications ($\rho_{(57)}$ = 0.86, 95%CI = 0.76 0.92, p = 1.94e-18; Figure 2C & S3). Indonesia, Kenya, Nigeria, and Venezuela had more users than would be expected given the number of publications originating there, whilst China, South Korea, and Taiwan had fewer. It should also be noted that interaction network nodes were located in 11 countries that had no publications at all (Table S3).

The number of tweets sent by users differed between regions ($H_{(7)}$ = 185.31, p = 0.0), with users in Africa sending the most per person (M = 3.0, IQR = 1.0-6.0, n = 24) and users in SE Asia the least (M = 1.0, IQR = 1.0-3.0, n = 101; Figure 2D). The number of interactions per tweet that a user had per tweet also differed between regions ($H_{(7)}$ = 85.08, p = 1.22e-15), with users in Africa having the most (M = 7.2, IQR = 4.0-12.1, n = 24) and East Asia the least (M = 2.0, IQR = 0.2-6.8, n = 108; Figure 2E).

Interaction networks

The full interaction network consisted of 8,578 nodes and 13,116 edges. Of these, 5,514 nodes had location information available (64.3%), connected by 7,750 edges (59.1%). The network of nodes with locations available had a lower maximum degree (M = 1, IQR = 1-2, range = 1-494) than did the network of nodes without (M = 1, IQR = 1-2, range = 1-528; $H_{(1)}$ = 8.59, p = 0.003) but the median degree and interquartile ranges matched and so the networks were deemed broadly comparable. A rich-club organisation was identified in both the full network and in the network of nodes for which there was location information (Figure S4).

The geographical distribution of the network is shown in Figure 3A. The 5% most important nodes were primarily located in Europe and North America (Figure 3B). This distribution was broadly proportional to the numbers expected given the total number of nodes per region (G = 12.07, p = 0.09; Figure S5). Nodes within Africa, Europe, and North America communicated more with other nodes within their own region (Figure 3C). In contrast, nodes in the remaining regions were more likely to communicate with nodes in other regions.

Interactive results

The data supporting the results presented can be explored in a Shiny app at https://russ-tmu.shinyapps.io/twitter_shiny/. There, readers can view user location patterns and interaction networks for specific conferences or years.

Discussion

The results present a mixed picture of Twitter engagement around the conferences studied. On the one hand, the number of tweets sent increased over time, with each tweet tending to be engaged with more over time also. This suggests that people are increasingly using the medium to create informal discussion around the events. On the other hand, the majority of users sent between one and three tweets, which may suggest a relatively shallow level of engagement. At the same time, the peak proportion of people engaging in this informal online communication via Twitter was only around a tenth of the actual conference attendees, which is comparable to previously reported Twitter engagement statistics (36, 37). It should be noted though that additional work would be required to judge if the level of engagement observed on Twitter was comparable or not to how people engage with in-person conference activities.

The conferences of 2020 and 2021 were held virtually due to pandemic restrictions (SfN was cancelled in 2020 and held virtually in 2021). A notable decrease in conference engagement of Twitter was observed for these years. Although the results reported do not provide insight into the reasons for this drop-off, a number of speculative explanations could be suggested. The first explanation would be that a general decrease in attendance for these virtual events compared to the years prior meant there were fewer people sending tweets. That FENS 2020, for example, had 4780 participants (38) compared to 7324 in 2018 (29) suggests that this is likely to have played a role. Note, however that this 35% decrease in attendance (assuming similar differences were seen for the other conferences) would not fully explain the over 50% reduction in tweet numbers between 2019 and 2021. A second potential explanation may be that the virtual events engender less engagement from participants than in-person ones and so they are less inclined to send tweets about them. This would fit with reports over the same period of fatigue and disengagement brought on by working online (39–41). A final potential explanation is that virtual events are successful in opening access for a more geographically diverse set of attendees and so are including more people outwith the regions where Twitter usage is concentrated, leading to a decrease in the proportion of attendees sending tweets. The true explanation is likely to include aspects of all these scenarios, amongst others, and will require additional data to understand fully.

Twitter engagement was seen across the globe, although the majority of users were located in Europe and North America. This pattern is not unexpected given the distribution of scientists involved in neuroscience research, as shown through a comparison with the number of relevant papers published by researchers in each country. It also reflects longstanding patterns of participation in international conferences (5). Exceptions to this pattern were seen for some countries, with Indonesia, Kenya, Nigeria, and Venezuela having more users than would be expected based on publication numbers and China, South Korea, and Taiwan having fewer. In the case of Indonesia, Kenya, Nigeria, and Venezuela, each country only had one or two publications and so their results should be treated with caution. China, South Korea, and Taiwan had considerably more publications and so the results in their case are likely robust. This relative under-representation is not unexpected in the case of China, where access to Twit-

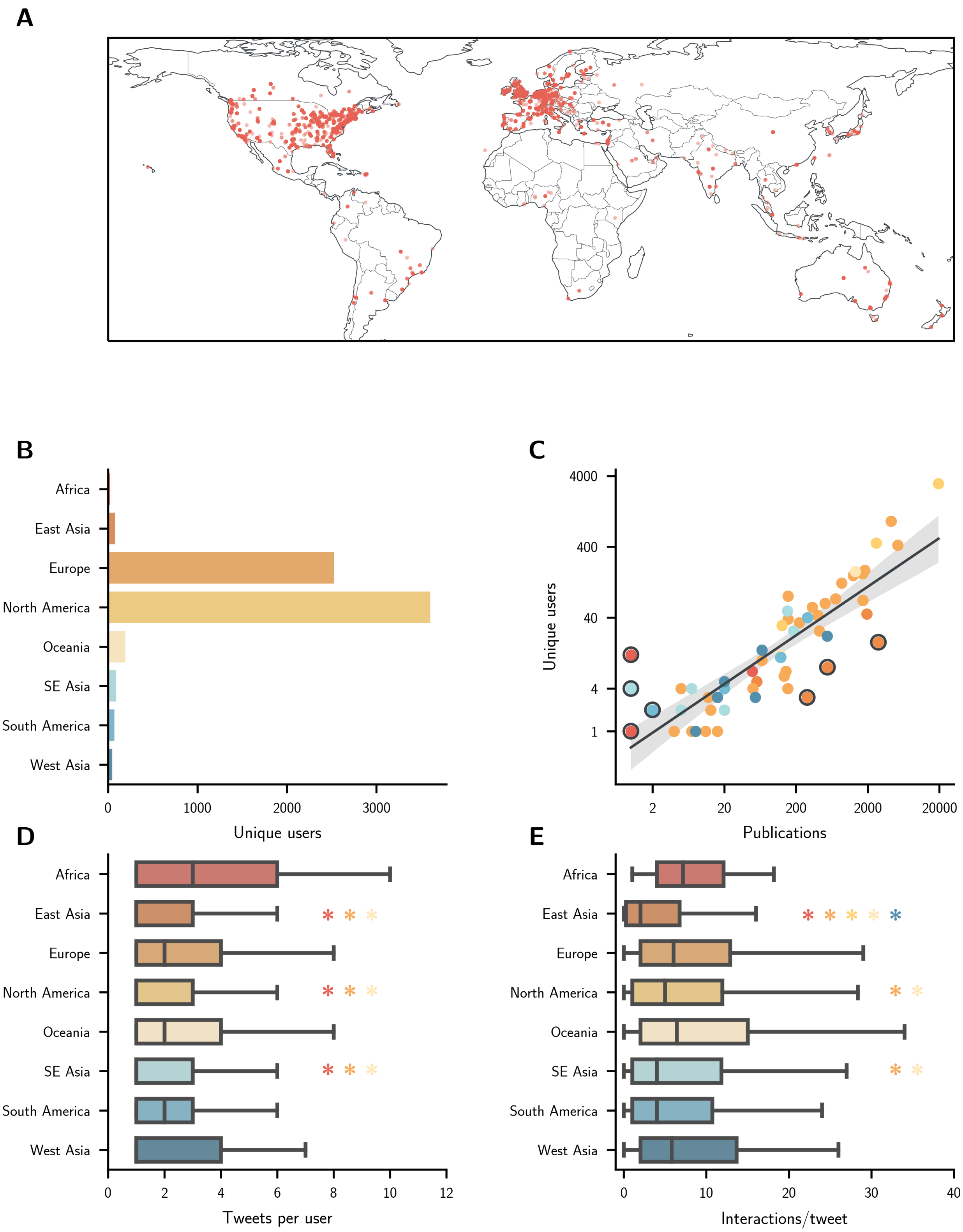

Figure 2. (A) Locations for unique users are indicated by a red dot. Note that users who give only a country as their location or who have had their city information removed will all appear at the same point within the relevant country. (B) Number of unique users per region. (C) Number of users per country plotted against number of publications on a log-log scale. The best-fit line is shown with a 95% confidence interval. Countries where the number of users is unexpected given the number of publications are highlighted in a dark circle. Countries are shaded according to their region. (D) Number of tweets sent per user. (E) Number of interactions/tweet. * denotes that the relevant metric for the marked region is lower than the region with the corresponding asterisk colour ($q < 0.05$)

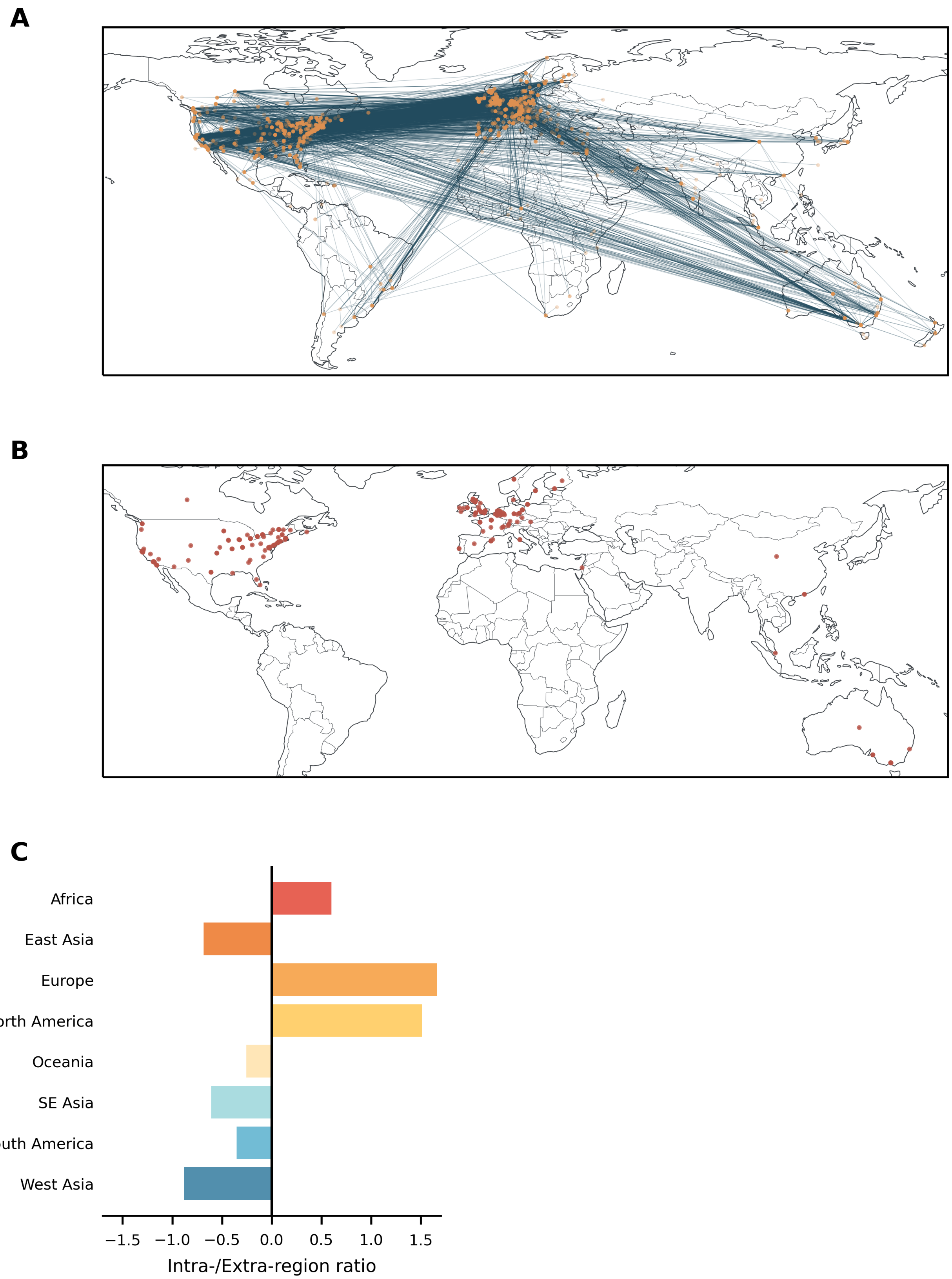

Figure 3. (A) Interaction network nodes (orange) and edges (blue). (B) Top 5% most important nodes for information transfer across the network are shown. Note that users who give only a country as their location or who have had their city information removed will all appear at the same point within the relevant country. (C) Ratio of intra-regional to extra-regional edges. Positive values denote a majority of intra-regional communication.

ter is limited to a privileged minority. No such restrictions apply in Taiwan or South Korea but in their cases social media services other than Twitter are more commonly used, meaning that researchers may be interacting in other ways.

As well as being fewer in number than would be expected, users in East Asia (i.e., China, Japan, South Korea, and Taiwan) sent fewer tweets and had fewer interactions with other users than did people in other regions. A similar effect was seen for users in South East Asia, although to a lesser degree. It is not clear what might be driving these differences but language may play a role. Many languages in these regions do not use Latin script and so the fact that the majority of tweets are in English may present a barrier to engagement. This language barrier has been noted as a reason for under-representation of East Asian scientists as speakers at conferences and may be being replicated in the virtual domain (42, 43).

An analysis of the conference interaction network showed that it follows a rich-club structure (32). This means that users tend to interact more with other users with the same number of connections or greater. This same structure has been reported in formal scientific collaboration networks (44), which are typified by a small number of influential individuals (45, 46). A survey of the users with most connections in the conference network found them to be prominent researchers within their field or to be the official accounts of scientific societies or related organisations (data not shown). This does not preclude, of course, that other users gain greater visibility through the Twitter network than they otherwise would (25). A rich-club-type structure was also observed in patterns of regional interaction directions. Users in Europe and North America were more likely to interact with other people within their own region. In contrast, users in the other regions were more likely to direct their interactions outwards. This suggests a flow from already less well represented regions towards already relatively privileged areas. Although suggestive, this result should not be overinterpreted though as information about the content of these interactions is not available.

A relevant factor when considering social media services in the context of organising global scientific networks is their status as private, for-profit companies (47). Their being so creates an ethical question around building networks where participation requires people to sign up to the terms of these services. In doing so they are generally required to give away access to their personal data, creating a tension between the privacy rights of individuals and the potential costs of not being able to participate in the network. At the same time, some social media companies have been highlighted as having negative effects on different societies (48, 49), resulting in a similar tension for those who may not wish to support the companies but do want to participate in the scientific network. Finally, what can and cannot be said on each service is dictated by the corporation and not the community (particularly where companies are subject to direct state censorship), which could lead to skewed scientific discussions and the exclusion of some community members. These ethical issues are unlikely to have any simple solutions, and the costs may be unavoidable, but they would appear to merit serious consideration.

Limitations

A number of limitation apply to the analysis. Firstly, user locations are based on what they report in their profile and so may not be accurate. Similarly, only one location per profile was used and so locations may reflect where someone was born, for example, rather than where they are currently located when both these locations were entered in their profile. More exact locations could be obtained through geolocation of tweets, but this information is (rightly) not publicly available. Secondly, it is possible that, although manual screening of tweets was conducted, some tweets that were unrelated to the conferences were included in the analysis. This is particularly true in the case of the network analysis where users may make mistakes when "tagging" people into a conversation. The relative number of unrelated tweets that may have been included is not, however, likely to be large enough to substantively change the patter of results. Finally, although the conferences studied include a large number of participants and cover a wide range of disciplines, the results may not generalise to conferences in other fields.

Conclusions

These results suggest that Twitter can play a role in informal communication around conferences but that there are potential limitations to its efficacy in this role. In particular, when considering the creation of networks around scientific events there is a need to consider geographical differences in online habits and access, as well as issues of language (16). These findings can be seen in the context of other work demonstrating the efficacy of virtual or hybrid conferences in making access more equitable by opening it up to those who have historically faced barriers to participation.

Data availability

Tweet information and publication location data are available at https://osf.io/46wh2/.

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Contributions

NWD: Conceptualisation, Formal Analysis, Investigation, Methodology, Visualisation, Writing – original draft
RS: Visualisation, Writing – review & editing

Conflict of interest

The authors declare no conflicts of interest.

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Supplementary materials

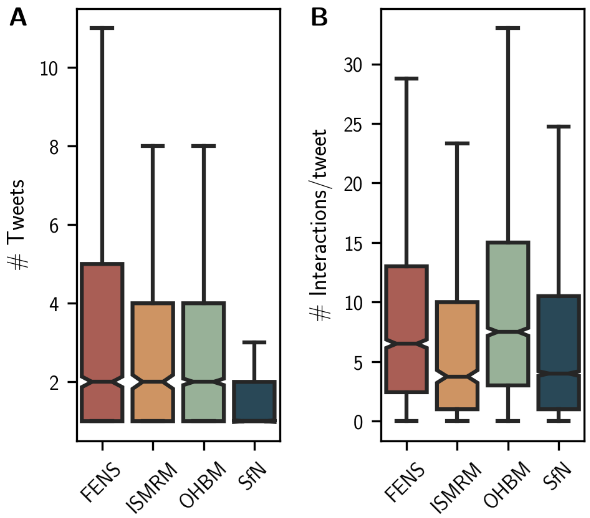

Figure S1. Number of (A) tweets sent and (B) interactions per tweet that each user had for each of the four conferences studied.

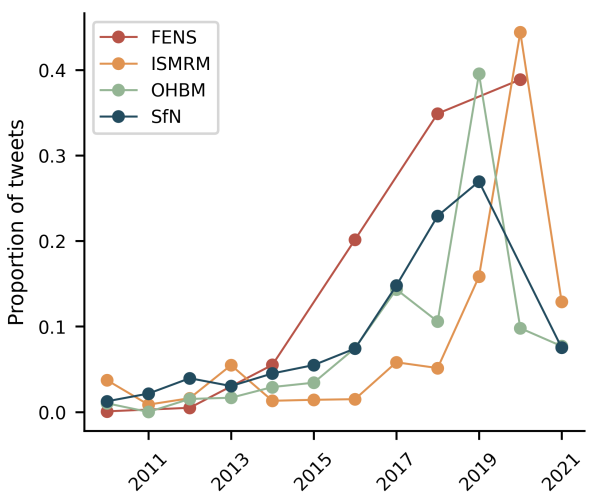

Figure S2. Number of tweets sent per year for each conference separately, normalised by the total number of tweets sent for that conference.

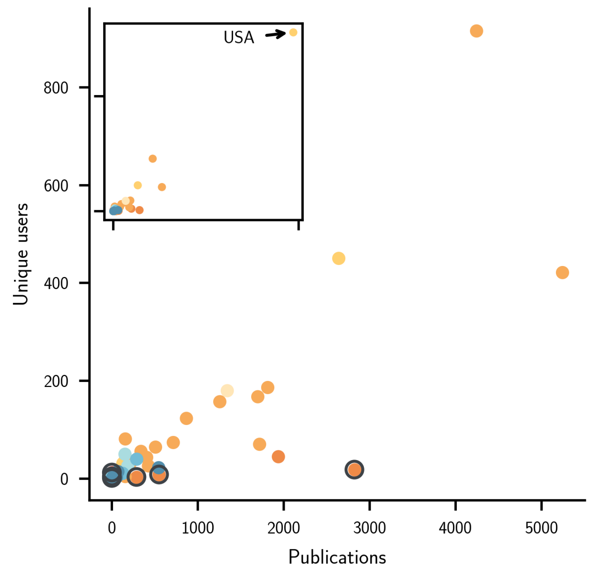

Figure S3. Publication and user numbers for each country plotted in original space. The main figure excludes the USA, with that country shown in the inset. Countries where the number of users is unexpected given the number of publications are highlighted in a dark circle. Countries are shaded according to their region.

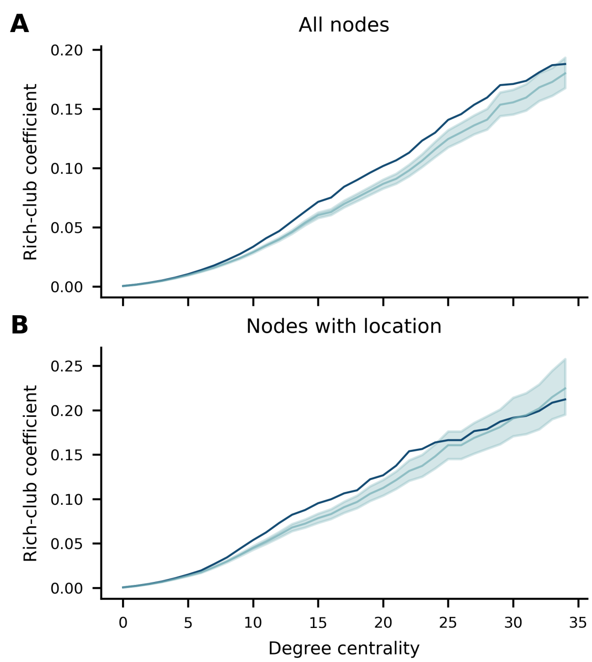

Figure S4. Rich-club coefficients (dark blue) at subsequent node degree centralities for (A) the whole network; and (B) the network composed of only nodes with location information. Rich-club coefficients from 500 randomised networks are shown in light blue, along with shaded 95% confidence intervals.

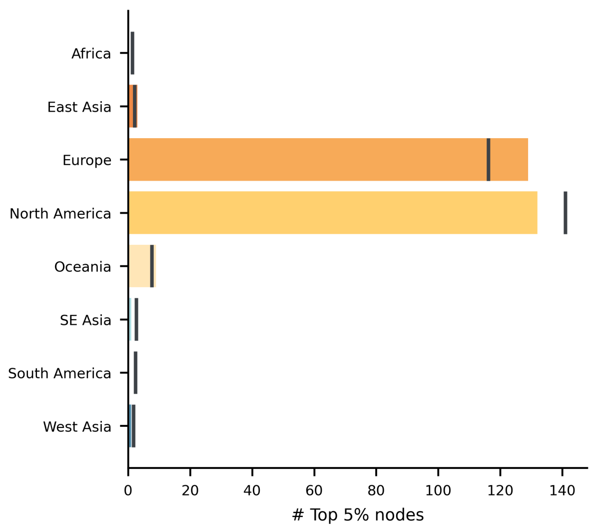

Figure S5. Number of top 5% important nodes per region. Expected numbers were important nodes to be distributed evenly across regions are shown with dark lines.

Region	Country	Region	Country	Region	Country
Africa	Ethiopia	Europe	Ireland	SE Asia	Bangladesh
	Ghana		Italy		India
	Kenya		Jersey		Indonesia
	Nigeria		Kosovo		Malaysia
	S Africa		Latvia		Nepal
	Tanzania		Lithuania		Pakistan
	Zimbabwe		Luxembourg		Philippines
	Algeria		Malta		Singapore
	Egypt		Netherlands		Sri Lanka
	Morocco		Norway		Thailand
East Asia	Cambodia		Poland		Vietnam
	China		Portugal	S America	Argentina
	Hong Kong		Romania		Brazil
	Japan		Russia		Chile
	Macao		San Marino		Colombia
	S Korea		Serbia		Dom. Republic
	Taiwan		Slovakia		Ecuador
Europe	Austria		Slovenia		Peru
	Belgium		Spain		Uruguay
	Bosnia		Sweden		Venezuela
	Bulgaria		Switzerland	West Asia	Iran
	Croatia		UK		Iraq
	Cyprus		Ukraine		Israel
	Czechia	N America	Canada		Kazakhstan
	Denmark		Costa Rica		Kuwait
	Estonia		Cuba		Lebanon
	Finland		Mexico		Oman
	France		Puerto Rico		Qatar
	Germany		USA		Saudi Arabia
	Greece	Oceania	Australia		Turkey
	Hungary		New Zealand		UAE
	Iceland				

Table S1. Region assignment for each country.

Journal	Publications	With location	Excluded
eNeuro	1581	1436	9.2%
Eur J Neurosci	4019	3930	2.2%
Front Hum Neurosci	6390	6318	1.1%
Front Neurosci	7042	7019	0.3%
Hum Brain Mapp	3692	3638	1.5%
J Neurosci	14796	13176	10.9%
Magn Reson Med	5196	5162	0.7%
NeuroImage	10970	10804	1.5%

Table S2. Publications with location information from each journal.

Country	Users
Bosnia and Herzegovina	2
Cambodia	1
Costa Rica	1
Ecuador	1
Ghana	1
Jersey	1
Latvia	1
Macao	1
Nepal	2
Peru	1
Puerto Rico	9

Table S3. Countries with Twitter users but no publications.