



An open data set of scholars on Twitter

Philippe Mongeon^{1,2} , Timothy D. Bowman³ , and Rodrigo Costas^{4,5} 

¹School of Information Management, Dalhousie University, Halifax, Nova Scotia, Canada

²Centre interuniversitaire de recherche sur la science et la technologie (CIRST), Université du Québec à Montréal, Montréal, Québec, Canada

³School of Information Sciences, Wayne State University, Detroit, MI, USA

⁴Centre for Science and Technology Studies (CWTS), Leiden University, Leiden, The Netherlands

⁵DSI-NRF Centre of Excellence in Scientometrics and Science, Technology and Innovation Policy (SciSTIP), Stellenbosch University, Stellenbosch, South Africa

an open access  journal



Citation: Mongeon, P., Bowman, T. D., & Costas, R. (2023). An open data set of scholars on Twitter. *Quantitative Science Studies*, 4(2), 314–324. https://doi.org/10.1162/qss_a_00250

DOI:
https://doi.org/10.1162/qss_a_00250

Peer Review:
https://www.webofscience.com/api/gateway/wos/peer-review/10.1162/qss_a_00250

Received: 23 August 2022
Accepted: 3 February 2023

Corresponding Author:
Philippe Mongeon
pmongeon@dal.ca

Handling Editor:
Vincent Larivière

Keywords: altmetrics, bibliometrics, open data, social media metrics, Twitter

ABSTRACT

The role played by research scholars in the dissemination of scientific knowledge on social media has always been a central topic in social media metrics (altmetrics) research. Different approaches have been implemented to identify and characterize active scholars on social media platforms like Twitter. Some limitations of past approaches were their complexity and, most importantly, their reliance on licensed scientometric and altmetric data. The emergence of new open data sources such as OpenAlex or Crossref Event Data provides opportunities to identify scholars on social media using only open data. This paper presents a novel and simple approach to match authors from OpenAlex with Twitter users identified in Crossref Event Data. The matching procedure is described and validated with ORCID data. The new approach matches nearly 500,000 matched scholars with their Twitter accounts with a level of high precision and moderate recall. The data set of matched scholars is described and made openly available to the scientific community to empower more advanced studies of the interactions of research scholars on Twitter.

1. INTRODUCTION

Engagement with academic research on social media has been a central research topic in scientometrics, particularly in altmetrics and social media metrics. In the early days of social media metrics research, the focus was primarily on investigating the relationship between the number of mentions of research publications on social media platforms (particularly Twitter) and citations, with most of the studies finding weak relationships between social media metrics and citations (Costas, Zahedi, & Wouters, 2014; Sugimoto, Work et al., 2017; Thelwall, Haustein et al., 2013). However, recent theoretical proposals have initiated a shift in the focus of altmetric research from analyzing mentions and correlations to more interactive perspectives. Thus, Haustein (2016) proposed that social media metrics need not be restricted to the mentions of scholarly outputs on social media but could also include the mentions and activities of individual scholars. More recently, Costas, Rijcke, and Marres (2021) proposed the notion of “heterogeneous couplings” as a common framework to study the interactions between academic and nonacademic actors as captured via online and social media platforms (see also Williams (2022)), in which the interactions of individual scholars on Twitter are another fundamental form of online interaction relating to how science is being communicated to society (Brainard, 2022).

Copyright: © 2023 Philippe Mongeon, Timothy D. Bowman, and Rodrigo Costas. Published under a Creative Commons Attribution 4.0 International (CC BY 4.0) license.



In the quest to study scholars' activities on Twitter, one long-lasting challenge is the identification of social media accounts belonging to researchers. In 2020 we published a paper that introduced a method to match Web of Science authors with their Twitter accounts (Costas, Mongeon et al., 2020) and reported on the distribution of scholars on Twitter across countries, disciplines, academic age, and gender. One of the main features of that data set was that it allowed us, for the first time, to investigate the relationship between the research profiles and activities of scholars and their profiles and activities on Twitter on a large scale (Ferreira, Mongeon, & Costas, 2021). Past data sets did not allow for this because they were either too small or because they provided information on whether or not a Twitter account *likely* belonged to a researcher without identifying the specific researcher to whom the account belonged.

Limitations of the data set we produced with this initial work included that it used proprietary data from the Web of Science and *Altmetric.com*, which made it impossible to share the author–tweeter pairs openly, and it was complicated for others to use the data set without access to these databases. The large number of steps involved in the previously reported process also possibly contributed to its lack of implementation by other researchers and its lack of transferability to other data sets.

New developments in Open Science scientometric and altmetric databases (namely the OpenAlex and Crossref Event Data databases) have changed this landscape, now allowing for the creation of matches of academic authors and their research publications with their Twitter profiles. This data paper aims to introduce a data set of scholars' Twitter accounts identified with a naïve algorithm based entirely on available open data, presenting the process in detail with accompanying R and Python scripts so that the process can be easily replicated and/or improved upon by the research community. We hope this data set will support further research on the interactions of scientific authors on social media and serve as a base for developing alternative and/or complementary approaches to match Twitter users and authors.

The paper is structured as follows. First, we provide an overview of the different data sources we used and the detailed process we used to match the Twitter accounts with OpenAlex authors. We then report precision and recall estimates for our matching approach, followed by an overview of the characteristics of the scholars found on Twitter.

2. DATA AND METHODS

2.1. Data Sources

2.1.1. OpenAlex

The research publications data source for this study is the OpenAlex (Priem, Piwowar, & Orr, 2022) data dump from May 20, 2022, which was downloaded and parsed into a relational database model hosted at the Maritime Institute for Science, Technology, and Society (MISTS) in Canada. In the OpenAlex database, authors are represented by a unique identifier (*author_id*) associated with their works (see the *works_authorships* table of the OpenAlex schema). The OpenAlex database we used contains 220,870,820 *author_ids*. Our ultimate objective is to assign a *twitter_id* to these *author_id* values. OpenAlex also includes a link between the *author_id* and ORCID. It is worth noting that a single individual can have multiple *author_ids* in OpenAlex, so that the same ORCID can be associated with multiple *author_ids*. It is not clear why authors with the same IDs are not merged together in the OpenAlex database, but it is likely due to the clustering approach used to construct the author entities. While we could have chosen to perform this merge ourselves as part of our process, we chose to use

all our data sources as they are and we did not merge any of the OpenAlex authors. It is always possible for the users of our data set to group OpenAlex authors together based on an author disambiguation process of their choice, which may include combining authors with the same ORCID.

2.1.2. Crossref Event Data

We use a data dump of Crossref Event Data from January 2022 available at the Centre for Science and Technology Studies (CWTS), containing over 60 million Twitter events from 5,288,867 unique Twitter accounts, which contain the tweet identifier and the DOI of the papers mentioned in that tweet. The dump includes 4.7 million unique DOIs tweeted at least once and recorded in Crossref Event Data (CED). We use the Twitter API to rehydrate the profile information of the Twitter users recorded in the CED dump. An important difference between CED and Altmetric is that CED focuses on identifying tweets to DOIs, while Altmetric also identifies Twitter mentions to preprints (e.g., from ArXiv) and other publication identifiers (e.g., PMIDs). Therefore, CED will typically identify fewer tweets to publications than Altmetric (Ortega, 2018).

Our use of an altmetric database such as Crossref Event Data to identify researchers on Twitter stems from the expectation, as in Costas et al. (2020), that researchers are more likely to tweet research publications than nonresearchers (Tsou, Bowman et al., 2015) and therefore to be recorded in this database. By considering only Twitter users that have mentioned scholarly work in their tweets as recorded in Crossref Event Data, we presumably increase precision at the expense of excluding all scholarly Twitter users that have never tweeted any research publications.

2.1.3. ORCID

The OpenAlex database includes the ORCID ids for approximately 2% of all the authors indexed in the database. Because some researchers include their Twitter handle in their public ORCID profiles, we leverage the information recorded in the ORCID Public Data File 2021 (Blackburn, Cabral et al., 2021) to retrieve the Twitter account for those researchers who self-reported a Twitter profile in their ORCID profile. We used the ORCID data dump (2021) hosted by the Centre for Science and Technology Studies (CWTS) to obtain a set of 13,208 matching OpenAlex author ids and ORCID profiles. This data set has been used as a golden set to evaluate the performance of our matching process. It should be noted that Twitter accounts listed in ORCID profiles are not necessarily valid. Even when these accounts are valid, it is important to note that the Twitter handle and user name may not include an actual name, which makes it impossible to match the accounts using the process described below as it relies on matching names. These factors may artificially penalize the recall, precision, and F-scores reported in the results section.

2.2. Matching Process

A central element in our current approach is the assumption that among the Twitter users tweeting a given publication, there will likely be one or more of the authors of that publication. Thus, this method is limited to identifying scholars on Twitter who tweeted (at least once) one of their publications (recorded on Crossref Event Data). This differs from the previous approach (Costas et al., 2020), which attempted to capture a broader range of relationships between Twitter users and authors to identify matches. This focus on “self-tweets” is likely to increase precision in matching authors and Twitter accounts but likely to decrease recall. However, we still expect to correctly identify a substantial number of authors on Twitter, as self-tweeting has been seen as an important form of researchers’ engagement on Twitter (Ferreira et al., 2021). This focus on self-tweets also has the advantage of being less complex and computationally intensive, thus more easily implementable and replicable by others.

2.2.1. Matching Twitter users with the authors of the tweeted papers

To identify tweeter–author pairs, we take every tweeted paper and attempt to determine whether one of the authors’ names matches the name of the Twitter user. An important feature of our approach to matching authors to Twitter users (similar to Costas et al. [2020]) is that researchers must, to some degree, use a similar form of their name in their Twitter profile name. Our process does not aim, and would not be able, to match the OpenAlex author id and the Twitter account of a researcher who uses a substantially different name in their Twitter and their authored works. For example, we will not match an author named Jane Smith using “squirrel1” as their Twitter profile name.

However, although we require some similarity between author names and Twitter names, they can be recorded differently in Twitter and OpenAlex (and from one OpenAlex author record to another). Name variations can include the use of initials instead of the full first name, the inclusion/omission of middle names in full or initial form, and the inclusion of extra characters representing professional titles (e.g., Dr., Ph.D., M.D.). This requires normalizing the names from both data sources to maximize the likelihood that valid matches will be identified. Following the process used by Mongeon, Robinson-Garcia et al. (2017) to match data set creators to Web of Science authors, we extract the last name(s), first name(s), and initial(s) of both Twitter users and OpenAlex authors and store them in distinct table columns. In those cases where a name contains more than two parts, we create an entry for all name combinations, assuming that all middle parts of the name can be part of the first or the last name. For instance, two entries would be created for the name John William Smith, one considering William as the second given name and one considering the token William as the first part of the last name. For each entry, we add a table column containing the initials (the first letter of each token that forms the first name), a table column containing the first initial only, and a table column containing the first token of the first name only.

The temporary tables used in the matching process include the unique ID of the individual (tweeter_id for Twitter and author_id for OpenAlex), the name, the deconstructed name variations, and the DOI tweeted in the event. Table 1 displays an example set of tweeter records.

We repeat the same process for OpenAlex authors and obtain a table like Table 2.

We use different matching steps with different levels of expected precision and recall ranging from exact matches on the full Twitter profile name and Author display name (highest expected precision) to matches between the first initial and the last name (lowest expected precision). We perform the same set of steps using the profile name and the handle name. However, because the handle names are a single string without spaces, for those matching attempts, we concatenate the parts of the author’s name in a single string as well. We also remove all nonalphabetical characters (e.g., underscore, space, numbers, and other special characters) from the handle name prior to the matching. Table 3 presents a list of attempted matches, including example matches.

3. RESULTS

Our results are divided into two parts. First, we report on the performance of our matching algorithm using the recall, precision, and F-score based on our golden set of authors with

Table 1. Example of a Twitter user record and extracted name components and variants

Tweeter_id	Handle	Profile name	First name	Last name	Initials	First initial	First token
12345678	jwsmith	John William Smith	John	William Smith	J	J	John
12345678	jwsmith	John William Smith	John William	Smith	JW	J	John

Table 2. Example OpenAlex record and extracted name components and variants

Author_id	Display name	First name	Last name	Initials	First initial	First token
12345678	John William Smith	john	william smith	j	J	john
12345678	John William Smith	john william	smith	js	J	john

an ORCID listed in OpenAlex and a Twitter handle in their ORCID account. In the second part, we describe our data set by presenting the distribution of authors with Twitter accounts across fields and countries.

3.1. Performance of the Matching Algorithm

We use the self-reported tweeter–author matches obtained from ORCID to evaluate the performance of the matching process at each step of the matching process. Precision is calculated by dividing the number of true positives by the total number of matches found for the tweeters in our golden set:

$$Precision = \frac{true\ positives}{true\ positives + false\ positives}$$

The recall is obtained by dividing the number of true positives by the total number of tweeter–author pairs in the golden set:

$$Recall = \frac{true\ positives}{true\ positives + false\ negatives}$$

The F-score is a measure of a model’s accuracy on a data set that is obtained with the following formula:

$$F = 2 \times \frac{precision \times recall}{precision + recall}$$

All three indicators take a value between 0 and 1, where 1 is the best possible score.

Table 3. Matching steps used to match Twitter profiles and OpenAlex author profiles

Step	Twitter data field	Examples
Full name exact match	Profile name	john william smith = john william smith
Full name substring*	Profile name	john smith = john smith Jr.
Last name + initials	Profile name	jw smith = jw smith
Last name + first token	Profile name	john w smith = john smith
Last name + first initial	Profile name	jw smith = j smith
Full name exact match	Handle	john william smith = johnwilliamsmith
Last name + initials	Handle	jw smith = jwsmith
Last name + first token	Handle	john w smith = johnsmith
Last name + first initial	Handle	jw smith = jsmith

* Note that the full name substring step is only performed with the Twitter profile name because preliminary attempts to search for the full name as a substring of the Twitter handle performed extremely poorly (F-score < 0.1).

Table 4. Results of the matching for each criterion

Matching step		Distinct matches			Test		
Criteria	Field	OpenAlex authors	Twitter accounts	Pairs	Recall	Precision	F-score
Last name + first token	Handle	24,929	21,755	24,929	0.041	0.981	0.078
Full name exact match	Handle	19,147	16,795	19,147	0.033	0.979	0.063
Last name + initials	Handle	13,577	11,693	13,579	0.021	0.977	0.041
Last name + first initial	Handle	8,528	7,247	8,530	0.012	0.976	0.024
Full name exact match	Profile name	307,270	272,409	308,880	0.423	0.971	0.590
Last name + first token	Profile name	419,805	368,832	422,341	0.553	0.971	0.705
Full name substring	Profile name	317,723	281,499	319,984	0.442	0.968	0.607
Last name + initials	Profile name	343,469	299,646	346,529	0.458	0.967	0.621
Last name + first initial	Profile name	471,763	406,389	477,383	0.593	0.961	0.734
Combined	Combined	492,142	423,924	498,680	0.623	0.958	0.755

Table 4 provides, for each of our matching criteria, the number of distinct matches obtained and the OpenAlex authors and Twitter accounts that form these matches, as well as the precision, recall, and F-scores obtained by testing each set of results against the golden set of author–tweeter pairs from ORCID.

Because the same pairs can be obtained at different precision steps, we report in Table 5 a different set of results where each step is performed hierarchically from most precise to least precise as per Table 4, and where each step considers only new pairs that were not identified in the previous ones. This does not change the overall result of the matching but provides a more unambiguous indication of the contribution of each step to the recall and precision. For instance, we can see that the lowest precision rate (0.80) is obtained when matching the last name and first initial with the tweeter’s profile name. This is consistent with the test results presented in Table 4. However, the difference in the precision between steps is more remarkable here because the count of true positives is not inflated by the valid matches from previous, more precise steps.

We can observe from Table 5 that the last three matching steps have a significantly lower precision rate than the other steps, especially the matches on the Last name + first initial between the author’s name and the tweeter’s profile name. This result was expected given that matching on the initials only would mean that an author named John Doe would match with both John Doe and Jane Doe. Perhaps more surprising is the still somewhat high levels of precision obtained. This is likely explained by our use of self-tweets only, which would match Jane Doe with John Doe only if Jane tweeted one of John’s papers. Still, researchers who might use our data set or our process are advised to exercise caution with these less precise matching steps. While the results presented here do not include any manual data validation, we performed such a validation for the matches obtained with the three least precise steps. The data set available on Zenodo (<https://zenodo.org/record/7013518>) includes a *validation* column alongside the *tweeter_id* and the *author_id* for the matches, which will allow users of the data set to use the entire set or to filter out the matches that our team identified as likely to be false positives. This data set also includes a column indicating which of the matching steps identified the match, so users of the data set can reconstruct a data set that does not include some of the steps, for instance.

Table 5. New matches identified at each step of the hierarchical matching process

Matching step Criteria	Field	Distinct matches			Test		
		OpenAlex authors	Twitter accounts	Pairs	Recall	Precision	F-score
Last name + first token	Handle	24,929	21,755	24,929	0.041	0.981	0.078
Full name exact match*	Handle	0	0	0	0	0	0
Last name + initials	Handle	13,325	11,513	13,327	0.020	0.976	0.040
Last name + first initial	Handle	1,976	1,758	1,976	0.003	0.966	0.006
Full name exact match	Profile name	83,862	251,936	285,373	0.380	0.971	0.546
Last name + first token	Profile name	96,587	87,508	97,088	0.101	0.964	0.182
Full name substring	Profile name	16,401	14,620	16,756	0.026	0.901	0.050
Last name + initials	Profile name	35,467	32,104	35,772	0.031	0.903	0.059
Last name + first initial	Profile name	22,989	20,815	23,459	0.017	0.806	0.033
Combined	Combined	92,142	23,924	498,680	0.623	0.958	0.755

* All matches obtained during the full name matching with the tweeter handle were also found in the previous step, meaning that this step could, in principle, be skipped. However, we keep the step in our process for consistency and to account for the possibility that this step might yield new matches in future implementations of the process.

Table 6 presents yet another variation of the hierarchical matching process reported in Table 5, with rows containing the cumulative matches so we can more clearly see how each step adds to the overall results.

3.2. Overview of the Data Set

In this section, we provide an overview of the composition of the data set by looking at the discipline and countries of the researchers for which we were able to assign a Twitter account. The main aim of these analyses is merely to provide a descriptive overview of the distribution

Table 6. Cumulative number of matches at each step of the hierarchical matching process

Matching step Criteria	Field	Distinct matches			Test		
		OpenAlex authors	Twitter accounts	Pairs	Recall	Precision	F-score
Last name + first token	Handle	24,929	21,755	24,929	0.041	0.981	0.078
Full name exact match	Handle	24,929	21,755	24,929	0.041	0.981	0.078
Last name + initials	Handle	38,248	33,201	38,256	0.061	0.979	0.115
Last name + first initial	Handle	40,223	34,841	40,232	0.064	0.979	0.120
Full name exact match	Profile name	323,935	286,528	325,605	0.445	0.972	0.611
Last name + first token	Profile name	420,167	369,257	422,693	0.548	0.970	0.700
Last name + initials	Profile name	436,170	382,820	439,449	0.574	0.967	0.720
Full name substring	Profile name	470,307	407,658	475,221	0.605	0.963	0.743
Last name + first initial	Profile name	492,142	423,924	498,680	0.623	0.958	0.755
Combined	Combined	492,142	423,924	498,680	0.623	0.958	0.755

of matches across publication disciplines and author countries. These overviews are meant to support future research and researchers interested in the data set, and to make users of the data aware of the general disciplinary and country representation of the data set.

There is no discipline classification in OpenAlex, but works are linked to Wikidata concepts (Priem et al., 2022), with a score ranging from 0 to 1 representing the strength of the association between the work and the concept. The concepts are hierarchical (levels 0 to 5), with level 0 essentially representing large disciplines (e.g., environmental science, economics, engineering, chemistry, medicine). More information about the concepts and their matching can be found on the OpenAlex website (<https://docs.openalex.org/about-the-data/concept>) and in this white paper (https://docs.google.com/document/d/1OgXSLriHO3Ekz0OYaoP_h0sPcuvV4EqX7VgLLbKe4/). For each unique author matched with a Twitter account, we retrieve their works and the level 0 concepts associated with these works, as well as the score. While these concepts are unlikely to provide a highly accurate classification of works, they are still helpful, we believe, in getting a sense of the breadth of disciplines represented in our data set. Table 7 shows the number and percentage of authors assigned to each discipline based on the discipline with the highest score based on all their

Table 7. Number of authors and the average score by discipline (concepts from OpenAlex)

Discipline	Number of authors	Percentage of authors	Average score
Medicine	138,968	28.3	0.517
Biology	75,246	15.3	0.388
Psychology	46,793	9.5	0.265
Computer science	39,675	8.1	0.201
Political science	36,531	7.4	0.229
Chemistry	30,876	6.3	0.242
Materials science	19,347	3.9	0.233
Environmental science	17,861	3.6	0.208
Business	17,485	3.6	0.158
Sociology	17,248	3.5	0.185
Geography	13,513	2.8	0.155
Economics	8,075	1.6	0.162
Geology	7,204	1.5	0.217
Physics	7,138	1.5	0.152
Art	6,963	1.4	0.133
History	3,913	0.8	0.134
Philosophy	2,415	0.5	0.097
Mathematics	1,637	0.3	0.068
Engineering	326	0.1	0.042
Total	491,214	100	

Table 8. Distribution of authors' last known affiliation recorded in OpenAlex

Country	Number of authors	Percentage of authors
United States	142,059	32.1
Great Britain	72,430	16.4
Australia	24,457	5.5
Canada	22,516	5.1
Spain	19,308	4.4
Germany	18,338	4.1
France	10,794	2.4
Netherlands	10,605	2.4
India	9,967	2.3
Italy	9,016	2.0
Brazil	7,330	1.7
Switzerland	6,251	1.4
Sweden	5,684	1.3
Ireland	5,382	1.2
Belgium	5,375	1.2
China	5,250	1.2
Finland	4,834	1.1
Denmark	4,543	1.0
Japan	4,361	1.0
Other countries	54,093	12.2
Total	442,593	100

publications. Because authors are associated with each discipline to some degree (represented by the average score of concepts in their publications), we also display the average score for each discipline as an alternate representation of the distribution of disciplines in the data set.

For the countries, we use the *last_known_affiliation* field of the OpenAlex *authors* table and present the relative frequency of countries in Table 8.

4. DISCUSSION AND CONCLUSION

The work presented in this paper can be framed as a step forward in developing more advanced studies of the interactions between science and society, particularly by enabling the study of the role of scientists in disseminating scientific results on Twitter. In addition, using open data sources (OpenAlex and Crossref Event Data) allows researchers to continue to improve and adapt this method for further possibilities without worrying about contractual limitations or data unavailability.

Overall, the results of our matching process show a high level of precision and a moderate level of recall, which was expected given our consideration of only self-tweets in the matching process.

This focus on self-tweets naturally makes a more precise matching strategy but at the expense of recall, as the method excludes from the matching all those scholars who never tweeted any of their publications (or none of their publications were included in the Crossref Event Data database).

The resulting matched database is more extensive than the one reported by Costas et al. (2020), which is most likely due to the broader coverage of OpenAlex compared to the Web of Science and improvements to the matching process. Other factors could include increasing Twitter use by researchers over time and/or increasing paper-sharing practices on Twitter or that more scholars are using their full names in their Twitter profiles.

It is important to emphasize the limitations of the matching approach (and resulting data set) presented in this paper. First, the approach is limited to tweets recorded in Crossref Event Data, which does not include tweets before 2017, and publications and researchers recorded in OpenAlex. Furthermore, our matching algorithm requires that names be written in the Latin alphabet, which may exclude some Twitter users or authors who are not using the Latin alphabet. On top of this limitation in the coverage of our data sources, our reliance on self-tweets to increase the precision of our matches comes at the expense of some degree of recall. While we find that this strategy does provide high precision levels, our examination of the data indicates that very common names can still generate some false positives. This provides some support for our choice not to cast a broader net by removing the self-tweet criterion, which would have likely flooded our data set with false positives for low expected gains in true positives and would also have dramatically increased the computational resources to perform the matching. It may also create a gender bias in our data set because a study by Peng, Teplitskiy et al. (2022) found men to be more likely to self-promote on Twitter than women. Finally, we also know from past research that there is a lower uptake of Twitter use in some regions or countries (Zahedi, 2017).

It is also worth mentioning here that our data set is limited to the matches that were created through the process, which uses only the names of the authors and the tweeters. There exist other sources of researcher–tweeter pairs that could be used to complement the data set. For instance, one could consider adding the data set of ORCID accounts with associated Twitter handles that we used as a golden set to validate our approach. OpenAlex also includes Twitter handles for a few hundred authors, although it is not clear what data source these pairs come from.

The characterization of the social media users and audiences that are engaging with scientific publications is an important element in the development of more advanced studies on the interactions between science and society. Thus, further and better curation of data around the interactions between social media users and academic objects is a fundamental step that needs to be considered in future altmetric research. Further developments of this work include expanding the matching to include additional matching criteria and developing approaches (e.g., citation or coauthor networks) to form tweeter–author pairs without relying only on self-tweets. Future developments could also tackle the challenge of matching scholars with Twitter users that did not tweet any publication. Nevertheless, we believe that the relatively simple matching process outlined in this paper and the open data set of nearly half a million pairs of OpenAlex author IDs and tweeter IDs generated and made available to the community are valuable contributions to the field of quantitative science studies, and more specifically to the study of the activities of scholars on Twitter and the interaction between social media and science.

ACKNOWLEDGMENTS

The authors would like to thank Poppy Riddle, Kydra Mayhew, and Maddie Hare, who helped with data cleaning.

AUTHOR CONTRIBUTIONS

Philippe Mongeon: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing—original draft, Writing—review and editing. Timothy D. Bowman: Conceptualization, Data curation, Formal analysis, Methodology, Writing—original draft, Writing—review and editing. Rodrigo Costas: Conceptualization, Data curation, Methodology, Writing—original draft, Writing—review and editing.

COMPETING INTERESTS

The authors have no competing interests.

FUNDING INFORMATION

Rodrigo Costas is partially funded by the South African DSI-NRF Centre of Excellence in Scientometrics and Science, Technology and Innovation Policy (SciSTIP).

DATA AVAILABILITY

The open data set of scholars on Twitter (Mongeon, Bowman, & Costas, 2022) produced with the process reported in this paper is available at <https://doi.org/10.5281/zenodo.7013518>. The data set includes a column indicating which criteria were successful in identifying the match, as well as a column indicating whether the match was considered valid upon manual inspection.

REFERENCES

- Blackburn, R., Cabral, T., Cardoso, A., Cheng, E., Costa, P., ... White, P. (2021). *ORCID Public Data File 2021* (p. 100806462894 Bytes) [Data set]. ORCID. <https://doi.org/10.23640/07243.16750535.V1>
- Brainard, J. (2022). Riding the Twitter wave. *Science*, 375(6587), 1344–1347. <https://doi.org/10.1126/science.abq1541>, PubMed: 35324287
- Costas, R., Mongeon, P., Ferreira, M. R., van Honk, J., & Franssen, T. (2020). Large-scale identification and characterization of scholars on Twitter. *Quantitative Science Studies*, 1(2), 771–791. https://doi.org/10.1162/qss_a_00047
- Costas, R., Rijcke, S., & Marres, N. (2021). “Heterogeneous couplings”: Operationalizing network perspectives to study science-society interactions through social media metrics. *Journal of the Association for Information Science and Technology*, 72(5), 595–610. <https://doi.org/10.1002/asi.24427>
- Costas, R., Zahedi, Z., & Wouters, P. (2014). Do “altmetrics” correlate with citations? Extensive comparison of altmetric indicators with citations from a multidisciplinary perspective. *Journal of the Association for Information Science and Technology*, 66(10), 2003–2019. <https://doi.org/10.1002/asi.23309>
- Ferreira, M. R., Mongeon, P., & Costas, R. (2021). Large-scale comparison of authorship, citations, and tweets of web of science authors. *Journal of Altmetrics*, 4(1), Article 1. <https://doi.org/10.29024/joa.38>
- Haustein, S. (2016). Grand challenges in altmetrics: Heterogeneity, data quality and dependencies. *Scientometrics*, 108(1), 413–423. <https://doi.org/10.1007/s11192-016-1910-9>
- Mongeon, P., Bowman, T., & Costas, R. (2022). Open dataset of scholars on Twitter [Data set]. *Zenodo*. <https://doi.org/10.5281/zenodo.7013518>
- Mongeon, P., Robinson-Garcia, N., Jeng, W., & Costas, R. (2017). Incorporating data sharing to the reward system of science: Linking DataCite records to authors in the Web of Science. *Aslib Journal of Information Management*, 69(5), 545–556. <https://doi.org/10.1108/AJIM-01-2017-0024>
- Ortega, J. L. (2018). Reliability and accuracy of altmetric providers: A comparison among Altmetric.com, PlumX and Crossref Event Data. *Scientometrics*, 116, 2123–2138. <https://doi.org/10.1007/s11192-018-2838-z>
- Peng, H., Teplitzkiy, M., Romero, D., & Horvát, E.-Á. (2022). The gender gap in scholarly self-promotion on social media [Preprint]. In review. <https://doi.org/10.21203/rs.3.rs-1765948/v1>
- Priem, J., Piwowar, H., & Orr, R. (2022). OpenAlex: A fully-open index of scholarly works, authors, venues, institutions, and concepts. *arXiv*, arXiv:2205.01833. <https://doi.org/10.48550/arXiv.2205.01833>
- Sugimoto, C. R., Work, S., Larivière, V., & Haustein, S. (2017). Scholarly use of social media and altmetrics: A review of the literature. *Journal of the Association for Information Science and Technology*, 68(9), 2037–2062. <https://doi.org/10.1002/asi.23833>
- Thelwall, M., Haustein, S., Lariviere, V., & Sugimoto, C. R. (2013). Do altmetrics work? Twitter and ten other social web services. *PLOS ONE*, 8(5), e64841. <https://doi.org/10.1371/journal.pone.0064841>, PubMed: 23724101
- Tsou, A., Bowman, T. D., Ghazinejad, A., & Sugimoto, C. (2015). Who tweets about science. In *Proceedings of ISSI 2015 Istanbul: 15th International Society of Scientometrics and Informetrics Conference* (pp. 95–100).
- Williams, K. (2022). What counts: Making sense of metrics of research value. *Science and Public Policy*, 49(3), 518–531. <https://doi.org/10.1093/scipol/scac004>
- Zahedi, Z. (2017). What explains the imbalance use of social media across different countries? A cross country analysis of presence of Twitter users tweeting scholarly publications (Version 2). *figshare*. <https://doi.org/10.6084/m9.figshare.5454475.v2>