Preregistration for Quantitative Research in Psychology (PRP-QUANT) Template

Title

T1 Title
The title should be focused and descriptive, using relevant key terms to reflect what will be done in the study. Use title case (https://apastyle.apa.org/style-grammar-guidelines/capitalization/title-case).
Academic #TwitterMigration to Mastodon: The Role of Influencers and the Open Science Movement

T2 Contributors, Affiliations, and Persistent IDs (recommend ORCID iD)
Provide in separate entries the full name of each contributor, each contributor's professional affiliation, and each contributor's persistent ID. See ORCID iD for an example of persistent ID (https://orcid.org/). Optional: include the intended contribution of each person listed (e.g. statistical analysis, data collection; see CRediT, https://casrai.org/credit/).
André Bittermann*, ZPID – Leibniz Institute for Psychology, Trier, Germany (https://orcid.org/0000-0003-2942-9831) Tim Lauer*, ZPID – Leibniz Institute for Psychology, Trier, Germany (https://orcid.org/0009-0003-1625-1672) Fritz Peters, ZPID – Leibniz Institute for Psychology, Trier, Germany (https://orcid.org/0009-0003-8471-4931) *shared first authorship

T3 Date of Preregistration
This is assigned by the system upon preregistration submission.

T4 Versioning information

This is assigned by the system upon submission of original and subsequent revisions. Should be a persistent identifier, if not a DOI.

T5 Identifier

This unique identifier is assigned by the system upon submission.

T6 Estimated duration of project

Include best estimate for how long the project will take from preregistration submission to project completion.

4 months

T7 IRB Status (Institutional Review Board/Independent Ethics Committee/Ethical Review Board/Research Ethics Board)

If the study will include human or animal subjects, provide a brief overview of plans for the treatment of those subjects in accordance with established ethical guidelines. If appropriate institutional approval has been obtained for the study, provide the relevant identifier here. If the study will be exempt from ethical board review, provide reasoning here.

This study was approved by the ethics committee of University of Trier (EK Nr. 59-2023).

T8 Conflict of Interest Statement
Identify any real or perceived conflicts of interest with this study execution. For example, any interests or activities that might be seen as influencing the research (e.g., financial interests in a test or procedure, funding by pharmaceutical companies for research).
None declared.

T9 Keywords
Include terms specific to your topic, methodology, and population. Use natural language and avoid words used in the title or overly general terms. If you need help with keywords, try a keyword search using your proposed keywords in a search engine to check results.
social impact theory, academic social networks, research community, social media, natural language processing, digital behavioral data, unobtrusive approach, metascience

T10 Data accessibility statement and planned repository
"We plan to make the data available (yes / no) If "yes", please specify the planned data availability level by selecting one of the options: ● Data access via download; usage of data for all purposes (public use file) ● Data access via download; usage of data restricted to scientific purposes (scientific use file) ● Data access via download; usage of data has to be agreed and defined on an individual case basis ● Data access via secure data center (no download, usage/analysis only in a secure data center) ● Data available upon email request by member of scientific community ● Other (please specify)
Other Due to copyright reasons, we will provide IDs for users and posts and add a guideline for dataset rehydration.

T11 Optional: Code availability
We plan to make the code available (yes / no). If "yes", please specify the planned code availability level (use same descriptors of data in T10).
Yes Code access via download; usage of data for all purposes (public use file)

T12 Optional: Standard lab practices
Standard lab practices refer to a (timestamped) document, software package, or similar, which specifies standard pipelines, analytical decisions, etc. which always apply to certain types of research in a lab. Specify here and refer to at the appropriate positions in the remainder of the template: We plan to make the standard lab practices available (yes / no). If "yes", please specify the planned standard lab practices availability level (use same descriptors of data in T10).
No

Abstract

(150 words)

A1 Background

(See introduction I1)

The acquisition of Twitter by Elon Musk in 2022, and the changes to the platform that came with it, started the so-called #TwitterMigration: Many users called for leaving Twitter and using alternative platforms like Mastodon.

A2 Objectives and Research questions

(See introduction I2)

Applying social impact theory, we hypothesize that academics on Twitter are more likely to migrate to Mastodon if they are under high social influence from #TwitterMigration influencers. We also hypothesize that researchers who endorse the open science movement are more likely to migrate to Mastodon than researchers who do not.

A3 Participants

(See methods M4)

We use an available dataset of around 500,000 researchers on Twitter, as well as lists of researcher accounts on Twitter and Mastodon. We identify additional researchers on Mastodon.

A4 Study method

(See methods M10-14)

For each researcher with posts related to #TwitterMigration, we compute an influence score. Open science advocates are identified using natural language processing. Based on account activity on both platforms, we identify users who have migrated to Mastodon.

Introduction

(no word limit)

I1 Theoretical background

Provide a brief overview that justifies the research hypotheses.

Twitter is one of the most popular academic social networks (e.g., Collins et al., 2016; Muscanell & Utz, 2017; van Noorden, 2014). However, the acquisition of Twitter by Elon Musk in October 2022, and the changes to the platform that came with it (such as less moderation of content and announced changes to the academic API access), started the so-called #TwitterMigration: Many (academic) users called for leaving Twitter and using alternative platforms (e.g., Nosek, 2022; Schönbrodt, 2022). In particular, the decentralized network Mastodon attracted a lot of attention and noted a high increase in user accounts starting at the end of October 2022 (Nicholas, 2022).

The Twitter migration to Mastodon has already been examined from several angles. Zia et al. (2023) tracked and analyzed the migration of 136,009 users, revealing that 2.26% of the users completely left Twitter (i.e., deleted their Twitter accounts). In addition, Mastodon appeared to be less toxic than Twitter in terms of rude, disrespectful, or unreasonable comments. Jeong et al. (2023) showed that platform migration patterns are most often characterized by users shifting their attention back to Twitter after creating a Mastodon account. La Cava et al. (2023) applied epidemic models to investigate the Twitter migration from an information diffusion perspective. They found that fewer social connections, engagement in discussions on Twitter migration, and shared identity in network communities play a pivotal role. Regarding scientists, Siebert et al. (2023) investigated the presence of highly-cited scientists on both platforms. They found that around 30% of them had Twitter accounts, and only 1% had Mastodon accounts.

To our knowledge, there is no study that has analyzed the academic #TwitterMigration from a psychological perspective. In general, scientists have been called upon and discussed as potential influencers and opinion leaders (Mojarad, 2017; Zhang & Lu, 2023). More specifically, the academic #TwitterMigration is an example of a social movement in academia that may have been driven by the persuasive processes of academic influencers. Persuasive processes in social networks might be explained with *Social Impact Theory* (Latané, 1981). According to this theory, the amount of social impact an individual experiences is the product of three social factors: strength, immediacy, and number of sources. Firstly, *strength* refers to how much power the influencing individuals have in terms of their social characteristics (e.g., socioeconomic status) and relationship with the target individual. Secondly, *immediacy* describes how recent or close the influence was. Lastly, *number of sources* refers to the amount of people influencing the target individual. With an increase in either of these three factors, the social impact on the target increases. In the case of multiple individuals being the target of influence, the social impact is distributed between them.

Nowadays, Social Impact Theory is one of the most widely used frameworks of social influence. Its application can also be found in various aspects of social media research spanning from influencer identification to the study of attitude change in a political context (e.g., Lin et al., 2019, Chang et al., 2018; Harton et al., 2022). Within this growing body of literature, different ways of operationalizing the three underlying factors of social impact have been used and suggested. For example, previous work has quantified the number of sources as the number of users creating topic-related posts (Mir & Zaheer, 2012), while another study has employed the number of likes as a measure (Ding et al., 2017). The remaining two concepts, immediacy and strength, have also found different realizations in previous work (e.g., Lin et al., 2019; Harton et al., 2022).

Previous social media research has been concerned with identifying so-called “influencers” and with designing metrics aimed to measure their influence. An influencer can simply be understood as a person that exerts great influence over others. Due to its nature, one of the most studied social media platforms in this context is Twitter: Compared to other major social media platforms, Twitter’s main purpose is the distribution of information (Bakshy et al., 2011). It is a microblogging platform that allows its users to share pictures, videos, and mainly text messages of up to 280 characters (140 until 2017). The core of early approaches in measuring influence on Twitter is the simple identification of influencers. This has been done by using indicators such as a user’s following/follower ratio or the repost behavior of their initial posts (e.g., Anger & Kittel, 2011; Bakshy et al., 2011). Over the years, such approaches have been extended to maximize the influence captured by the identified influencers, for example, by minimizing the overlap between them in the network (e.g., Zareie et al., 2018). Mongeon and colleagues (2023) identified around 500,000 scholars on Twitter. Their data has previously been used as a metric for their academic impact. Moreover, mining scientific communication on twitter has shown the ability to predict future publication trends (Bittermann et al., 2021). Hence, previous research has applied the measuring of influence to academic social networks (e.g., Li & Gillet, 2013).

In November 2022, open science supporters called for the #TwitterMigration and #NovemberMigration pledge (e.g., Nosek, 2022; Schönbrodt, 2022). Under these hashtags, they asked Twitter users to shift their social media activity from Twitter to Mastodon. Similar to Twitter, Mastodon is a microblogging platform that focuses on short written toots (i.e., tweets) that can be reposted by other users (for a detailed description of Mastodon, see Zulli et al., 2020). However, Mastodon is a decentralized social media platform that is not profit oriented. It consists of different servers that each have their own moderation policies and often are subject-specific. Mastodon does not hide behind several layers of abstraction. Its development is done by its users which includes coding, “developments of icons, graphics, documentation, and policies” (Zulli et al., 2020, p. 1194). Furthermore, Mastodon does not employ abstract algorithms to shape the stream of content seen by its users. These properties of Mastodon are consistent with the goals of open science, which is based on the principles of transparency and accessibility (Vicente-Saez & Martinez-Fuentes, 2018). Open science is a movement that aims to produce high quality research which is openly shared throughout the different steps of the research cycle (American Psychological Association, 2018). It is based on the following principles: transparency, inclusivity, accessibility, reproducibility. Given the role of shared identity in subgroups in the Twitter migration (La Cava et al. (2023), it is reasonable to assume that the open science movement within academia may be particularly supportive of the migration.

I2 Objectives and Research question(s)

Outline objectives and research questions that inform the methodology and analyses (below).

In this study, we extend the knowledge of influencers in academic social networks and investigate whether the open science community supports the migration to Mastodon. Based on this use case, we discuss implications for the diffusion and implementation of innovations in the research community.

I3 Hypothesis (H1, H2, …)

Provide hypothesis for predicted results. If multiple hypotheses, uniquely number them (e.g., H1, H2a, H2b,) and refer to them the same way at other points in the registration document and in the manuscript.

H1: Researchers who are under higher social influence from #TwitterMigration influencers are more likely to migrate to Mastodon than researchers who are under lower social influence.

H2: Researchers who endorse the open science movement are more likely to migrate to Mastodon than researchers who do not.

I4 Exploratory research questions (if applicable; E1, E2, ...)

If planning exploratory analyses, provide rationale for them here. If multiple exploratory analyses, uniquely number them (E1, E2, ...) and refer to them in the same way in the registration document and in future publications.

None

Method

M1 Time point of registration
Select one of the options: ● Registration prior to creation of data ● Registration prior to any human observation of the data ● Registration prior to accessing the data ● Registration prior to analysis of the data ● Other (please specify; might include if T1 longitudinal data has been analyzed, but T2 has not yet been analyzed)
Other ● Due to Twitter's short notice announcement on February 2, 2023 that free API access will no longer be supported after [February 9, 2023](#) (which was subsequently extended several times), we collected tweets, profiles, and follower lists from February 2 to June 23. ● The data was stored on a server with limited access and was not analyzed prior to this pre-registration, with the following exception: ○ Twitter's API for retrieving follower information is very limited: Followers can only be retrieved for 15 users every 15 minutes (see [here](#)). While it would be desirable to have the complete follower network of all researchers in this study, this would take approximately 350 days for 500,000 users. As the future of academic access to the Twitter API was unclear at the time of writing this pre-registration, we decided to retrieve follower information only for academic influencers in the context of #TwitterMigration. ○ To this end, we collected all tweets containing specific keywords related to Twitter migration (i.e., “TwitterMigration”, “TwitterExit”, “TwitterExodus”, “JoinMastodon”, “MastodonMigration”, “ScienceMastodon”, “AcademicMastodon”, “Mastodon”). We then retained only original Tweets by researchers, discarding all others. Researchers were identified using the “open dataset of scholars on Twitter” (Mongeon et al., 2022). ○ Next, we aimed to identify influencers by calculating an ***influence score*** between 0 and 1 for each person. This score was a weighted sum of several global metrics (followers count, listed count) and local metrics (number of retweets, likes, and mentions for tweets containing at least one of the keywords). We examined how different weights for the global and local metrics impacted the distribution of influence scores and the top 100 most influential people. Ultimately, we chose to assign a low weight to global metrics (20%) and a high weight to local metrics (80%), favoring topic-specific influence related to Twitter migration. We then ranked the researchers by their influence scores and started to scrape their followers from the Twitter API, beginning with the most influential and progressing to the least influential individuals (see M12).

M2 Proposal: Use of pre-existing data (re-analysis or secondary data analysis)
Will pre-existing data be used in the planned study? If yes, indicate if the data were previously published and specify the source of the data (e.g., DOI or APA style reference of original publication). Specify your level of knowledge of the data (e.g., descriptive statistics from previous publications), whether or not this is relevant for the hypotheses of the present study, and how it is assured that you are unaware of results or statistical patterns in the data of relevance to the present hypotheses.
For researchers on Twitter, we use the "open dataset of scholars on Twitter" (Mongeon et al., 2022; https://doi.org/10.5281/zenodo.7013518) and the list of Twitter and Mastodon accounts "OpenCheck" For Mastodon profiles we retrieve academics from the Academics on Mastodon repository on GitHub. These data sources contain user ids which we use to query the API and retrieve profile information (e.g., user name, location, profile description). We have no knowledge of Tweet contents, specifically w.r.t. #TwitterMigration.

Sampling Procedure and Data Collection

M3 Sample size, power and precision
(1) Relevant sample sizes: e.g., single groups, multiple groups, and sample sizes (or sample ranges) found at each level of multilevel data. (2) Provide power analysis (e.g. power curves) for fixed-N designs. For sequential designs, indicate your 'stopping rule' such as the points at which you intend to be viewing your data and in any way analyzing them (e.g., t-tests and correlations, but even descriptively such as with histograms).
We'll analyze data of all available users.

M4 Participant recruitment, selection, and compensation
Indicate (a) methods of recruitment (e.g., subject pool advertisement, community events, crowdsourcing platforms, snowball sampling); (b) selection and inclusion/exclusion criteria (e.g., age, visual acuity, language facility); (c) details of any stratification sampling used; (d) planned participant characteristics (gender, race/ethnicity, sexual orientation and gender identity, SES, education level, age, disability or health status, geographic location); (e) compensation amount and method (e.g., same payment to all, pay based on

performance, lottery).

Researchers are identified using the data sources described in section M2. In addition, we will leverage the fact that some Mastodon users include their account handles in their Twitter account names or profile descriptions. Moreover, we may identify additional researchers on Mastodon as described in AP3.

M5 How will participant drop-out be handled?

Indicate any special treatment for participants who drop out (e.g., there is follow-up in a manner different from the main sample, last value carried forward) or whether participants are replaced.

Not applicable

M6 Masking of participants and researchers

Indicate all forms of masking and/or allocation concealment (e.g., administrators, data collectors, raters, confederates are unaware of the condition to which participants were assigned).

Not applicable

M7 Data cleaning and screening

Indicate all steps related to data quality control, e.g., outlier treatment, identification of missing data, checks for normality, etc.

We will screen the data for inconsistencies related to the API retrievals. For example, we will remove duplicates, if any, among the collected user profiles and social media posts, separately for each platform (Twitter, Mastodon). Further, we will remove unnecessary information from the data (e.g., columns with irrelevant data). For more detailed information on data preprocessing, see AP3.

M8 How will missing data be handled?

Indicate any procedures that will be applied during the analysis to deal with missing data, such as (a) case deletions; (b) averaging across scale items (to handle missing items for some); (c) test of missingness (MAR, MCAR, MNAR assumptions; (d) imputation

procedures (FIML vs. MI); (e) Intention to treat analysis and per protocol analysis (as appropriate).
Only cases with full data will be considered (i.e., data on publication activity on both platforms)

M9 Other information (optional)

For example, training of raters/participants or anything else not yet specified.

1. Data collection

We queried the Twitter API (academic access in early 2023; see M1) to retrieve

- tweets related to #TwitterMigration,
- profile information for users who posted on #TwitterMigration,
- follower information for users who posted on #TwitterMigration,
- profile information for researchers IDs provided by Mongeon et al. (2022) and account lists (M2), and
- researcher timelines for November and December 2022 (in order to examine account activity during the initial #TwitterMigration phase), and April 2023 (to investigate a potential return to Twitter in 2023, see AP8).

The Mastodon API will be queried to retrieve

- Posts that contain the hashtag #Introduction (as it is a common practice on Mastodon instances to introduce oneself) to generate a training set of researchers and non-researchers (AP3),
- profile information of researchers and non-researchers who are identified via #Introduction posts on Mastodon (M1, M4) and account lists (M2),
- follower information for identified researcher accounts in order to identify further academics (M4),
- researcher timelines for 2022 and April 2023 (to investigate a potential return to Twitter in 2023).

It is important to note that we will only use data from Mastodon instances whose terms of service do not prohibit data collection for research purposes.

Examining account activity on both platforms is necessary to determine if there has been an actual "migration", i.e. more activity on Mastodon than Twitter (see M12).

2. Data protection

Even though the collected data are public behavioral traces in online social media, we keep them strictly confidential. During data analysis, plain names are removed from the data sets and stored in a separate table. The assignment of names is then only possible via numerical pseudonyms. The plain name table is stored separately, password-protected and only accessible to the project manager. The other persons involved in the data analysis thus work with pseudonymized data.

To ensure the rules of good scientific practice, the raw data are stored for at least ten years. They are stored in electronic form and secured against any access by external persons. In accordance with the General Data Protection Regulation (GDPR), we'll take technical and organizational measures to prevent unauthorized access to data.

For long-term archiving purposes, only Post_IDs or User_IDs (by which researchers with access to the APIs authorized by the platforms can rehydrate the data) with "Access Class 1 (Scientific Use File)" are archived on a repository such as PsychArchives and are expected to remain available for at least ten years.

Social media data is dynamic. Profiles or individual posts may have been deleted by users in the meantime. If this is the case and our research group is aware of it, we delete the corresponding entries in the data sets. If this means that the reproducibility of the results is limited, we point this out at the appropriate places. In this conflict between open science and data protection, the decision is thus in favor of the latter.

Conditions and design

M10 Type of study and study design

Indicate the type of study (e.g., experimental, observational, crosssectional vs. longitudinal, single case, clinical trial) and planned study design (e.g., between vs. within subjects, factorial, repeated measures, etc.), number of factors and factor levels, etc..

observational study
with unobtrusive measurement of digital behavior traces

M11 Randomization of participants and/or experimental materials

If applicable, describe how participants are assigned to conditions or treatments, how stimuli are assigned to conditions, and how presentation of tests, trials, etc. is randomized. Indicate the randomization technique and whether constraints were applied (pseudo-randomization). Indicate any type of balancing across participants (e.g., assignments of responses to hands, etc.).

Not applicable

M12 Measured variables, manipulated variables, covariates

This section shall be used to unambiguously clarify which variables are used to operationalize the hypotheses specified above (item I3). Please (a) list all measured variables, and (b) explicitly state the functional role of each variable (i.e., independent variable, dependent variable, covariate, mediator, moderator). It is important to (c) specify for each hypothesis how it is operationalized, i.e., which variables will be used to test the respective hypothesis and how the hypothesis will be operationally defined in terms of

these variables. The description here shall be consistent with the statistical analysis plans specified under AP6 (below).

Independent variables:

IV1 Social Impact: continuous predictor, z-standardized
Operationalization:
According to Social Impact Theory (Latané, 1981):
Social Impact = Strength x Immediacy x Number of Sources.

For *Strength* (salience, importance, or intensity of influencing source), we use the *influence score* metric with range 0-1.

> (see M1: For each academic with original posts related to #TwitterMigration: Weighted sum of 20% global metrics (followers count, listed count) and 80% local metrics (number of retweets, likes, and mentions for tweets containing at least one of keywords related to #TwitterMigration). If one has the maximum across all global and local metrics, the score is 1.)

Specifically, strength is defined as the mean influence score of followees.

For *Immediacy* (proximity of influencing source), we focus on social proximity in terms of similar interests. Specifically, for each user, we will:

1. Extract hashtags*: Extract the max. top 100 most frequently used hashtags for each user (excluding hashtags related to #TwitterMigration, see M1).
2. Calculate embeddings: Use a transformer model (i.e., RoBERTa) to calculate embeddings for each of these hashtags for each user.
3. Weight the embeddings: Multiply the embeddings by their corresponding hashtag frequency to give more weight to the hashtags that a user uses more often.
4. Aggregate embeddings: For each user, average the weighted embeddings of their top 100 hashtags to get a single vector that represents the user's interests.
5. Calculate similarity values: Using these aggregated vectors, calculate cosine similarity (range 0-1) between each pair of users to get their social immediacy scores.
6. Calculate mean similarity score.

   * To obtain hashtags of the users, we will use the tweets or Mastodon posts collected for November/December (2022) (see M9), depending on the person's main social media outlet.

The *Number of (influencing) Sources* is the number of #TwitterMigration influencers that the user is following on Twitter, scaled to range 0-1 (min/max).

All three factors will be included in a linear model (see AP6).

IV2 Open Science Endorsement: binary predictor (yes/no)
Operationalization:
Users are regarded as endorsing open science if they

- state "Open Science" or grammatical variants in profile descriptions (without negation), or
- post on open science with a positive sentiment (in average across their max. top 100 posts)

For this, we will use a transformer model fine-tuned for sentiment analysis (Twitter-roBERTa-base for Sentiment Analysis).

Dependent variable:

DV Migration to Mastodon: factor with two levels (yes/no).
Operationalization:
According to Treibel (2008), migration means that people shift their center of life over a longer period of time.
Hence, a user is counted as Mastodon migrant if, during the initial period of the #TwitterMigration on Twitter (i.e., during November and December, 2022),

- a new account is created or an existing account is revitalized (i.e., no posts on Mastodon in 2022 before November 2022), and
- Mastodon is used more actively by the user than Twitter (i.e., more posts on Mastodon)

Covariates:

In order to control for potential confounding effects, we will include several covariates (see below). The covariates will be z-standardized .

Followers Count: continuous covariate, z-standardized
Following Count: continuous covariate, z-standardized
Account Age: continuous covariate, z-standardized
Tweet Count: continuous covariate, z-standardized

M13 Study Materials

Please describe any relevant study materials. This could include, for example, stimulus materials used for experiments, questionnaires used for rating studies, training protocols for intervention studies, etc.

Not applicable

M14 Study Procedures

Please describe here any relevant information about how the study will be conducted, e.g., the number and timing of measurement time points for longitudinal research, the number of blocks or runs per session of an experiment, laboratory setting, the group size in group testing, the number of training sessions in interventional studies, questionnaire administration for online assessments, etc.

Not applicable

M15 Other information (optional)

Analysis plan

(NOTE: If this varies by hypothesis, repeat analysis plan for each)

AP1 Criteria for post-data collection exclusion of participants, if any
Describe all criteria that will lead to the exclusion of a participant's data (e.g. performance criteria, non-responding in physiological measures, incomplete data). Be as specific as possible.
We will exclude bot accounts, if any, among the most influential Twitter accounts w.r.t. #TwitterMigration. To identify bots, we will use tools like tweetbotornot and manual checks of positive bot classification.

AP2 Criteria for post-data collection exclusions on trial level (if applicable)
Describe all criteria that will lead to the exclusion of a trial or item (e.g. statistical outliers, response time criteria). Be as specific as possible.
We will exclude duplicate items, if any, returned by the APIs or due to the use of software packages for querying the APIs. We will use unique identifiers like id, conversation id, author id, and content to ensure no relevant information (e.g., reposts) is removed.

AP3 Data preprocessing
Describe all data manipulations that are performed in preparation of the main analyses, e.g. calculation of variables or scales, recoding, any data transformations, preprocessing steps for imaging or physiological data (or refer to publicly accessible standard lab procedure, T12).
<u>Academic influencer identification for Twitter dataset</u> The academic Twitter accounts in this study are based on the 'open dataset of scholars on Twitter' provided by Mongeon et al. (2022) and publicly available account lists of accounts (see M2). To ensure the validity of actual *academic* accounts, we will manually inspect the profile descriptions (and, in case of doubt, perform a web search) of the top 100 most influential individuals. <u>Researcher identification on Mastodon</u> Siebert et al. (2023) found that the number of Twitter accounts of highly-cited scientists is about 30 times higher than the number of Mastodon accounts. Roughly estimated, this means that around 500,000 / 30 ≈ 16,600 academic Mastodon accounts can be expected (Mongeon et al.’s dataset of scholars on Twitter contains around 500,000 accounts). In light of this estimation, we proceed as follows in order to identify as many researchers on

Mastodon as possible:

First, we will make use of open lists of Mastodon accounts (that are already matched with Twitter accounts; see M2). Second, we will check for Mastodon account handles in Twitter profiles and screen names (La Cava, 2023). The sum of unique Mastodon accounts will be compared to the above-mentioned estimation (i.e., 16,600 accounts) in order to decide whether a third source for finding Mastodon account names might be necessary. In this case, we will use the following approach to identify additional researchers on Mastodon:

Researchers on Mastodon will be identified using ground truth data sources (see M2) and network crawling using a chain-referral sampling algorithm (as used in Müller et al., in press):

1. The friends and/or mentions network (depending on Mastodon API rate limits) of a seed dataset of verified researchers (see above) is crawled.
2. Researcher accounts in the network are identified through natural language processing based on their profile descriptions: We compare
    a. **simple pattern matching** (e.g., “scientists”, “researcher”) to
    b. transformer-based **zero-shot classification** and, in case of insufficient performance (AP3),
    c. a **text classification model** trained on a ground–truth dataset of verified researcher and non-researcher accounts.
3. For all identified academics in step 2, the friends and/or mentions network is retrieved.
4. Steps 2 and 3 are repeated until no more researcher accounts can be found in the network.

Note, non-researcher accounts will be obtained using a three-step approach: We will first apply pattern matching to the pool of #Introduction posts (M1) in order to pre-select posts not likely to be made by researchers. We will then apply pattern matching to the corresponding profile descriptions, retaining those profiles that are less likely to belong to scientists. To generate training, validation, and test sets, a subset of these profiles will then be manually evaluated as to whether they indeed do not belong to scientists based on their profile descriptions.

Terms to be used for pattern matching (considering grammatical variants):
    “researcher”, “phd”, “scientist”, “academic”, “scholar”, “lecturer”, “prof”, “post-doc”, “post-graduate”, “graduate student”

Candidate labels to be used for zero-shot classification:
    We’ll inspect classification performance of different labels (or multiple labels) like: “researcher”, “scientist”, “academic”, “scholar”, “lecturer”, “professor”, “phd student”, “grad student”, “postdoc”

Zero-shot model:
    We will initially use facebook’s “bart-large-mnli” model for zero-shot classification and may consider using other models to improve performance. Moreover, we may explore ensemble techniques to aggregate predictions. Specifically, we may predict classes separately for each candidate label and then use majority voting based on model performance to make final predictions, potentially enhancing robustness.

Text classification model:
    We will initially utilize embeddings from pre-trained transformer models, starting with relatively small models like “roberta-base” or “distilbert-base-uncased”, and

train classic machine learning models on these embeddings (e.g. Logistic Regression). In order to improve the performance, we will consider using larger embeddings (e.g., “roberta-large”) and/or more complex models (e.g., Gradient Boosting Machines). We may also consider fine-tuning a pre-trained transformer model for text classification, starting with a small model like “distilbert-base-uncased”.

To compare zero-shot and supervised learning models, we will adopt the following evaluation strategy:

- Data splitting: We will split our ground-truth dataset into a training set, validation set, and test set. The training set will be primarily used to train the supervised model. The validation set will serve two main purposes: fine-tuning the parameters of the supervised model and optimizing the decision threshold for both the supervised and zero-shot models. Note, we may use cross-validation techniques where feasible.
- Model evaluation: Our primary objective is to achieve high precision to minimize false positives while maintaining reasonable recall. The final model performance will be assessed on the held-out test set.

Overlap between Twitter and Mastodon dataset

For further analysis, it is necessary to identify the overlap between Twitter and Mastodon accounts. Specifically, we will use three approaches to match Twitter and Mastodon accounts:

- **Ground truth dataset:** We will use the “OpenCheck” and “academics on mastodon” lists as our ground truth, containing users who have voluntarily shared their Twitter and Mastodon account information.
- **Pattern matching**: We will expand the ground truth dataset by including Twitter accounts that have explicitly mentioned their Mastodon account handles in their Twitter account names or profile descriptions.
- **Predictive matching**: For accounts where ground truth is not available, we will consider using a predictive matching approach: We will first establish a baseline using pattern matching, based on the rationale that a user's Twitter and Mastodon name or handle are likely to be similar. We will then explore ways to improve this baseline, possibly using different machine learning techniques and profile features.

  To evaluate the effectiveness of different predictive matching approaches, we will create a training set, validation set, and test set from the ground truth dataset. Each set will comprise both matching and non-matching account pairs. Note, Mastodon handles will be removed from these Twitter profiles as they are not available during inference. As a starting point for improving the baseline, we will use transformer (e.g., RoBERTa) embeddings for user names/handles and profile descriptions.

  Cosine similarity will be calculated for each pair of accounts in the training set. We will plot the precision-recall curve to examine the precision-recall trade-off at various thresholds. Our goal is to achieve high precision, minimizing false positives, while maintaining reasonable recall. An initial threshold will be chosen based on this criterion, and its performance will be validated using the validation set. Our primary evaluation metric will be precision, and we will adjust the threshold accordingly based on the validation set results. The final threshold will be evaluated on the test set. Note that, before assessing precision on the validation set, a post-processing step will be applied to ensure that each Twitter account is matched with at most *one* Mastodon account: Starting with the Twitter account with the highest similarity score, it will be assigned to the corresponding Mastodon account, which will then be removed from the pool of potential matches for all other Twitter accounts.

This process will be repeated for all remaining Twitter accounts. However, we recognize that some Twitter users might have multiple Mastodon accounts. We may therefore adjust this condition during the validation phase, permitting a Twitter account to be matched with multiple Mastodon accounts. During testing as well as inference, this post-processing step will be reapplied. To ensure that high precision is maintained during inference, we will employ a sample-based precision analysis: a sample of 100 randomly selected predicted account matches will be inspected, and precision will be calculated accordingly. It should be noted that the predictive matching approach is complex and potentially challenging, with its effectiveness highly dependent on the quality and consistency of account naming practices and profile descriptions across platforms. Consequently, if the precision of our predictive matching technique falls below a predefined threshold of 0.95 during the initial testing phase, we will limit our analysis to the accounts identified through the ground truth datasets.

Social impact on migrating users (see M12)
Open Science Endorsement (see M12)

AP4 Reliability analysis (if applicable)

Specify the type of scale reliability that will be estimated, whether it is internal consistency (e.g. Cronbach's alpha, omega), test-retest reliability, or some other form (e.g., a confirmatory factor analysis incorporating multiple factors as sources of variance). In a study involving measure development, researchers should specify criteria for removing items from measures a priori (e.g., largest factor loading magnitude, smallest drop in alpha-if-item removed).

not applicable

AP5 Descriptive statistics

Specify which descriptive statistics will be calculated for which variables. If appropriate, specify which indices of effect size will be used. If descriptive statistics are linked to specific hypotheses, explicitly link the information given here to the respective hypothesis.

- Number of users Twitter vs. Mastodon
- Number of posts Twitter vs. Mastodon in November/December 2022
- Number of migrated users
- Number of influencers and their characteristics

- Number and proportion of users that endorse open science among migrating academics and influencers

AP6 Statistical models (provide for each hypothesis if varies)

Specify the statistical model (e.g. t test, ANOVA, LMM) that will be used to test each of your hypotheses. Give all necessary information about model specification (e.g., variables, interactions, planned contrasts) and follow-up analyses. Include model selection criteria (e.g., fit indices), corrections for multiple testing, and tests for statistical violations, if applicable. Wherever unclear, describe how effect sizes will be calculated (e.g., for d-values, use the control SD or the pooled SD).

<u>Statistical Models:</u>
We will use a logistic regression model for both hypotheses:

$$\text{Logit}(P(Y=1)) = \beta 0 + \beta 1*(\text{Social Impact}) + \beta 2*(\text{Open Science Endorsement}) + \beta 3*(\text{Follower Count}) + \beta 4*(\text{Following Count}) + \beta 5*(\text{Account Age}) + \beta 6*(\text{Tweet Count}) + \varepsilon$$

Where:

- $P(Y=1)$ is the probability of a user migrating to Mastodon.
- β0 is the intercept, representing the log odds of migrating for a user with mean values for all z-standardized continuous predictors and at the reference level for the binary predictor 'Open Science Endorsement' (no endorsement).
- β1 and β2 are coefficients for the predictors, representing the change in log odds of migrating for a one standard deviation increase in 'Social Impact' or a change from absence to presence of 'Open Science Endorsement, holding all other predictors constant.
- β3 through β6 are coefficients for the covariates, also representing the change in log odds of migrating for a one standard deviation increase in the corresponding covariate, holding all other variables constant.
- ε is the error term.

In addition, we will conduct an exploratory analysis, assessing the unique contributions of social impact factors by including them as separate predictors. We may then also consider exploring interactions between different social impact factors.

$$\text{Logit}(P(Y=1)) = \beta 0 + \beta 1*(\text{Strength}) + \beta 2*(\text{Immediacy}) + \beta 3*(\text{Number of sources}) + \beta 4*(\text{Open Science Endorsement}) + \textit{Covariates} + \varepsilon$$

<u>Model Selection:</u>
Given our hypotheses, a logistic regression model is well suited as it allows us to model the binary outcome of migration as a function of our predictors and covariates. Given our pre-planned model and hypotheses, we will not engage in post hoc model selection procedures or corrections for multiple testing.

<u>Tests for Statistical Violations:</u>
We will check for potential violations of the logistic regression assumptions, including multicollinearity among predictors. Initially, we will assess the relationships among our proposed predictors and covariates ('Social Impact', 'Open Science Endorsement', 'Followers Count', 'Following Count', 'Account Age', 'Tweet Count') by calculating pairwise correlation coefficients and Variance Inflation Factors (VIFs). If we observe correlations

above 0.7 between pairs of variables or VIFs exceeding 5 for any variable, we will consider this an indication of potential multicollinearity. We will then consider different strategies to address this, such as combining correlated variables into a single composite variable or dropping one or more of the variables. We may also consider using statistical techniques that can handle multicollinearity, such as ridge regression or lasso regression. Moreover, we may consider implementing a weighted logistic regression approach to handle potentially severe class imbalance of the dependent variable by using weights that are inversely proportional to class frequencies. Once potential violations are addressed, we will proceed with our main analysis. Our logistic regression model would then include the main predictors 'Social Impact' and 'Open Science Endorsement' and the adjusted covariates.

Effect Sizes:

We will report the odds ratios associated with the predictors, 'Social Impact' and 'Open Science Endorsement', along with their respective 95% confidence intervals. These odds ratios, computed as the exponentials of the corresponding coefficients (i.e., $e^\wedge\beta_1$ and $e^\wedge\beta_2$), signify the change in odds of migrating for a one standard deviation increase in 'Social Impact' or a change from absence to presence of 'Open Science Endorsement', while holding all other variables constant. Confidence intervals for these odds ratios will be calculated using the standard error of the coefficient and the normal approximation to the sampling distribution of the coefficient.

AP7 Inference criteria

Specify the criteria used for inferences (e.g., p values, Bayes factors, effect size measures) and the thresholds for accepting or rejecting your hypotheses. If possible, define a smallest effect size of interest. If inference criteria differ between hypotheses, specify separately for each hypothesis and respective statistical model by explicitly referring to the numbers of the hypotheses. Describe which effect size measures will be reported and how they are calculated.

Inferences will be drawn based on the 95% confidence intervals for the odds ratios of the predictor variables 'Social Impact' and 'Open Science Endorsement'. The null hypothesis for each predictor is that the associated odds ratio is equal to one, implying no effect on the odds of migration to Mastodon. This null hypothesis will be rejected if the 95% confidence interval for the odds ratio does not include one.
For 'Social Impact', we hypothesize that the associated odds ratio will be greater than one, indicating an increased likelihood of migrating to Mastodon for a one standard deviation increase in social impact. For 'Open Science Endorsement', we also hypothesize that the associated odds ratio will be greater than one, suggesting that endorsing the Open Science movement (changing from the reference category of no endorsement to endorsement) increases the likelihood of migration.
Effect sizes will be reported as odds ratios, calculated as the exponentiated coefficients from the logistic regression model. The 95% confidence interval for the odds ratio will be derived from the confidence interval for the associated coefficient. Given the novelty of the #TwitterMigration phenomenon, we do not have a predefined smallest effect size of interest.

AP8 Exploratory analysis (optional)
Describe any exploratory analyses to be conducted with your data. Include here any planned analyses that are not confirmatory in the sense of being a direct test of one of the specified hypotheses.
● Open Science Endorsement: To get more insights in the role of the Open Science Movement, we will conduct an NLP-based analysis of OSM posts in the context of #TwitterMigration, e.g., exploring top terms and sentiment. ● To investigate whether academics may have returned to Twitter, we plan to compare publication activity on both platforms for April 2023.

AP9 Other information (optional)

Other information optional

(NOTE: If needed, multiple lines with other information can be included)

O1 Other information (optional)
If there is any additional information that you feel needs to be included in your preregistration, please enter it here. Literature cited, disclosures of any related work such as replications or work that uses the same data, or other context that will be helpful for future readers would be appropriate here.

References

R1 References

Enter your references below. Use a consistent format (e.g., https://apastyle.apa.org/style-grammar-guidelines/references/examples)

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