Can We Count on Social Media Metrics? First Insights into the Active Scholarly Use of Social Media

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ABSTRACT

Measuring research impact is important for ranking publications in academic search engines and for research evaluation. *Social media metrics*, or *altmetrics*, measure the impact of scientific work based on social media activity. Altmetrics are complementary to traditional, citation-based metrics, e.g. allowing the assessment of new publications for which citations are not yet available.

Despite the increasing importance of altmetrics, their characteristics are not well understood: Until now it has not been researched what kind of scholars are *actively* using which social media services and why – important questions for scientific impact prediction. Based on a survey of 3,430 scientists, we uncover previously unknown and significant differences between social media services: We identify services which attract young and experienced researchers, respectively, and detect differences in usage motivations. Our findings have direct implications for designing future altmetrics for scientific impact prediction.

KEYWORDS

social media, digital scholarship, altmetrics, motivations

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1 INTRODUCTION

The use of the web is an integral part of scientific work. On social media, researchers discover new research, discuss research ideas with fellows and disseminate research results to the public and to the scientific community [7, 9, 21]. Additionally, academic search engines support scientists in finding scholarly literature.

In order to improve their performance, academic search engines employ *scholarly metrics*: citation-based measures for the scientific impact of authors and scientific works [1]. In fact, scholarly metrics are also important for other applications such as hiring decisions and project and application evaluation [23, 26].

One drawback of traditional, citation-based metrics is that citations are not available for new publications – the first citation of a paper may take years. Additionally, scholarly metrics do not cover the impact of scientific publications on the web. Therefore, *social media metrics* or *altmetrics* were introduced as a complement to traditional metrics: By analysing usage patterns on social media, altmetrics evaluate the quality of scholarly products through their impact on the web [21]. Altmetrics which predict the *scientific* impact of scholarly work [32] will likely play a central role in many future applications such as scientific literature retrieval.

Current altmetrics data providers such as *altmetric.com* or *PlumX* use sums [6] or simplistic weightings [27] for aggregating altmetrics from different social media services. For instance, view counts are aggregated across services using (arbitrarily weighted) sums. It has not yet been investigated whether this practice reflects the diversity of users on social media. In order to improve altmetrics for scientific impact prediction, it is essential to understand the demographics and motives of scholarly social media users. If social media services differ significantly in the demographics or motives of their users, the mechanisms of altmetrics would have to be improved: One example could be a service-specific correction for the share of postdocs, who are known to have a high productivity [5] and thus create more citations, which are to be predicted.

This paper analyses the results of a survey among 3,430 scientists, providing first insights into the scholarly use of social media by detecting and describing **(i) demographic differences of active scholarly users of social media** and **(ii) variations in the motivation for scholarly use of social media** between services.

It is well-known that a small share of active users in social media contributes the majority of observed activities, the so-called "90:9:1 rule" [17]. As a result, active users are responsible for most of the activities measured by altmetrics. Unlike previous analyses of the scholarly use of social media [9, 32], **we therefore only consider *active* users** who use social media at least weekly for scientific purposes.

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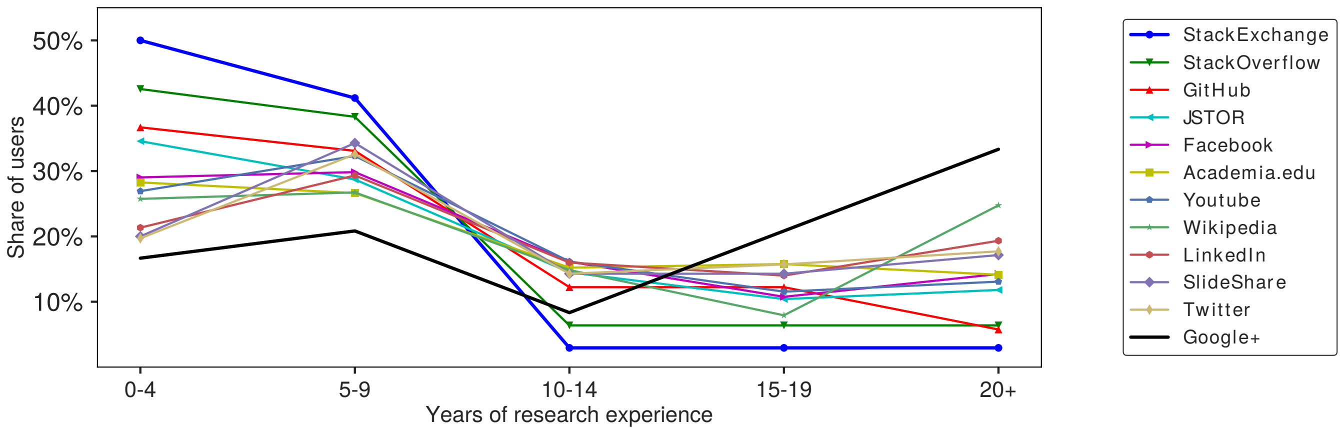


Figure 1: Academic experience of active users per service. Q&A and programming-related services (StackExchange, StackOverflow, GitHub) are more popular with young scientists, while networking services (Google+, Twitter, LinkedIn), SlideShare and Wikipedia have the highest percentage of experienced scientists. The legend shows services ordered by their share of young scientists (0-4 years of experience). The services with the highest share of young researchers (StackExchange) and the highest share of experienced academics (Google+) are highlighted. Social media services show substantial differences in the experience level of active scholarly users.

2 RELATED WORK

Social media have become increasingly popular for scholarly communication [19, 28]. Several metrics based on scholarly social media activities have been shown to correlate with traditional, citation metrics [14, 32], though previous studies have pointed out that there is wide variability in the social media use of researchers. Differences have been observed in age, academic role, discipline and country, among others [4, 7, 13, 16, 22].

Using metrics based on social media activities comes with various challenges such as the assurance of data quality, the variety of users and their motivations in social media, and the prevention of bias [3, 8]. One key problem of scholarly social media data is the systematic bias towards scholars with certain demographic characteristics such as bias towards younger users [20] and towards users with a professional interest in research [15]. Several studies state that the lack of accurate user statistics or sample descriptions for social media sites complicates the quantification of these biases [3, 26].

Scholars use social media for various reasons. Van Noorden [30] identified multiple categories of motivations for scholarly social media use: *contacting peers, posting content, sharing links to authored content, actively discussing research, commenting on research, following discussions, tracking metrics, discovering jobs, discovering peers, discovering recommended papers, offering a contact possibility* and *curiosity*. Jordan [9] identified motivation categories by manually coding questions asked by researchers on Academia.edu.

It is well known that a small minority of active social media users is responsible for a large share of activities [10, 31]. Russo et al. [24] give an overview of multiple studies on various social media sites and Kunegis [11] shows statistics for dozens of social networks, all confirming the effect. To the best of our knowledge, there is no study on the demographics and motivations of *active* scholarly users on social media.

3 DATA AND METHODS

We analyse data from an exploratory online survey on the professional scholarly use of social media, which we conducted as part of a larger research project on metrics. Our survey provides detailed insights into user activities by including questions on the intensity and the extent to which social media services and their interactions (e.g. like, share or post) are used. Analysing the stated frequency of interactions enables us to identify active users.

In total, the survey contains 20 questions; among others, we asked participants for their research experience, their academic role, the social media services they use, and how often and why they are using social media services. The full questionnaire is available online[1].

3.1 Survey data

Our survey on social media usage was distributed via multiple channels: Authors who had at least one publication after 2015 with an email listed in the Web of Science[2] or RePEc[3] and multiple mailing lists related to Economics, Social Sciences or its subfields were contacted. As the survey was conducted as part of an interdisciplinary project involving partners from economics and social sciences, our main target group was economists and social scientists.

More than 3,430 international researchers participated in our survey from March to May 2017 with a response rate of about 6%. Most of the researchers are from the fields of economics (60%) and social sciences (22%). Researchers from 84 countries participated, the majority of them from Germany (51%), followed by the US (10%), the UK (5%) and Italy(5%). Participants were 19 to 89 years of age (median age 38). The distribution of academic roles is as follows: About 44% of the participants are professors, followed by PhD students / research assistants (31%) and postdocs (19%).

[1]https://github.com/marymm/-metrics/raw/master/questionnaire.pdf
[2]http://apps.webofknowledge.com
[3]http://repec.org

This is in line with studies showing that professors together with PhD students have the highest share of profiles on academic social media [13, 18].

More than half of the participants – 1,731 researchers – use at least one interaction (e.g. like, share or post) of a social media service per week. We call these researchers *active users*.[4]

Though our sample is not representative, the high share of active users in our survey allows us to analyse differences between social media services. If we find significant differences between services in our survey, we also expect to find differences in the parent population.

3.2 Experience differences and motivations

In our survey, we asked participants to state their research experience since graduation using predefined ordinal categories (0-4 years etc.). For detecting significant differences in the distribution of research experience, we look at all possible pairs between the twelve most-mentioned services and use pairwise χ^2 tests on category counts of the answers of participants. We apply the Benjamini-Hochberg procedure with a false discovery rate of 0.05 and only pairs with strong effect sizes (> 0.25) were considered. Using answers on a question on participants role in academia (options include professor, postdoc, PhD student / research assistant), we applied the same statistical test to detect significant differences in the distribution of academic roles between pairs of services.

Our survey contains a question on reasons for using social media. In order to detect latent motivations for using social media, we ran Latent Dirichlet Allocation (LDA) [2], the most common topic model, on the free text answers. Topic models detect sets of semantically related words using the co-occurrence of words in documents. We chose to set the topic parameter to 10 topics (the lowest number yielding meaningful topics), and used sparse, symmetric document-topic and topic-word Dirichlet priors with $\alpha = \beta = 0.1$. Changing the Dirichlet parameters to other common sparse values did not change the topics significantly. Negative answers (e.g. "none") were manually deleted and stopwords (from NLTK [12]) were removed from the remaining answers, resulting in 997 answer texts.

4 RESULTS

In this section, we look at differences between social media services in terms of demographics and motivations of active users.

4.1 Research experience

To check for demographic differences between the active users of services, we plot the distribution of research experience among active users for the twelve most-frequently named services, shown in Figure 1. We find that services for software development and question and answering – StackExchange, StackOverflow and GitHub – have the highest share of young researchers. On the other hand, services for networking like Google+, Twitter and LinkedIn as well as services for spreading research and information to the general public, like SlideShare and Wikipedia, have a far higher share of

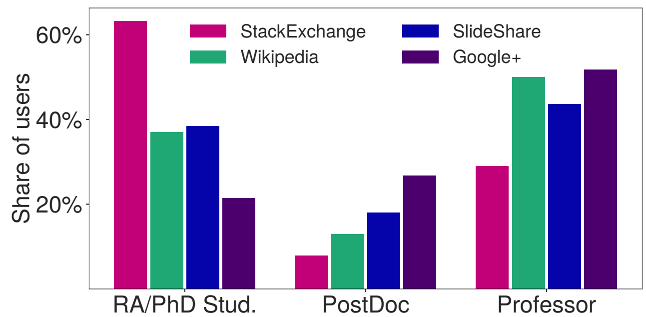


Figure 2: Role distribution of active scholarly users for selected services. We found strong differences between services: StackExchange is mostly used by research assistants and PhD students, while in our survey Google+, SlideShare and Wikipedia are mainly used by Professors. While the share of professors is roughly the same for Wikipedia and Google+, the share of post docs is twice-as-high for Google+, indicating a relationship between role and service use.

experienced researchers. We identified multiple pairs of services with significant differences and large effect sizes (> 0.25): The difference between StackExchange and Google+ is significant (p-value 0.00005), as well as the difference to LinkedIn. Additionally, Google+ is significantly different from StackOverflow and GitHub. Another pair with significant differences is GitHub-Wikipedia. This is the first evidence that research experience influences the active scholarly use of social media. Altmetrics based on social media with a focus on software development will be biased towards young researchers, metrics on services mainly used for networking will be biased towards the actions of experienced researchers.

To take a closer look at this finding, we compare the distribution of academic roles between services with significant differences in user experience in Figure 2. Google+ and Wikipedia have the highest share of experienced users. Looking at their distribution of academic roles, we see that Wikipedia has twice as many PhD students as Google+, while the latter has about twice as many postdocs compared to Wikipedia. The distributions of Google+ and StackExchange are significantly different (p-value: 0.0001).

Both findings indicate that different social media services fulfill different demands and thus both role and experience distributions of their users vary.

4.2 User motivations

The motivations for using social media are known to vary among scholars [9, 30]. In our survey, we asked researchers to name reasons for using social media. We ran LDA [2] on their answers to detect these latent motivations.

Table 1 shows the detected topics. By looking at the top words of the topics and at answers with high topic probabilities in the corpus, we found that the topics can be interpreted as follows: *Topic 0*: sharing and accessing papers of peers/other people, *Topic 1*: users who think that their research is relevant to others, *Topic 2*: finding and sharing interesting works, *Topic 3*: getting information on new

[4]We found active users to show different characteristics compared to other participants. For instance, the share of inexperienced researchers (0-4 years of academic experience after graduation) is slightly higher for active users (33%) compared to others (29%).

topics, *Topic 4*: spreading interesting results, *Topic 5*: showing interesting topics to the community, *Topic 6*: downloading articles, *Topic 7*: sharing relevant research with friends, *Topic 9*: promoting important work of colleagues. *Topic 8* repeats the words from the question, indicating an influence of the question on the answers. We therefore ignore this topic in our analysis.

In order to check whether there are differences between user motivations between the different services, we compare the topic distributions of the active users for different services. A user can be active in multiple services. The global topic distribution is shown in Figure 3a. To find services with strong differences, we show the difference from the global topic distribution for services with a significant difference in user experience in Figure 3b.

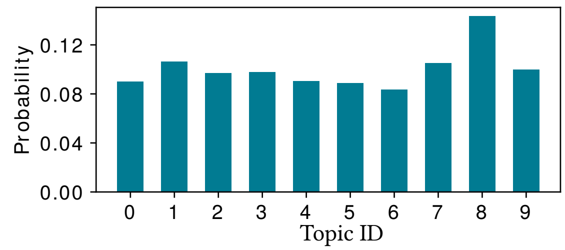
We see that different social media services meet different needs: StackExchange has less users who want to find interesting academic works (Topic 2) and more active users who want to share research with friends (Topic 7) and to get new information (Topic 3). In contrast, Wikipedia has a below-average share of users who want to share relevant research with friends or their community (Topic 5 and 7), but they like to share relevant research and interesting findings with a general audience (Topic 1 and 2). Similarly, SlideShare has an above-average share of users who use social media because they think that their research is relevant for others (Topic 1) and they like to spread interesting results (Topic 4) but have a lower probability for sharing content in their community (Topic 5 and 7). Finally, Google+ has a higher share of users who want to share relevant research with friends but a lower probability for promoting work of colleagues (Topic 9).

These findings contribute to the understanding of the patterns found in Figure 1: Google+ attracts relatively more scholars who want to share their research – and this could explain why we see a higher share of professors / experienced users. StackExchange attracts more users who search for information – and we can assume that this causes a high share of research assistants and PhD students, who have more practical duties and a higher need for question answering services.

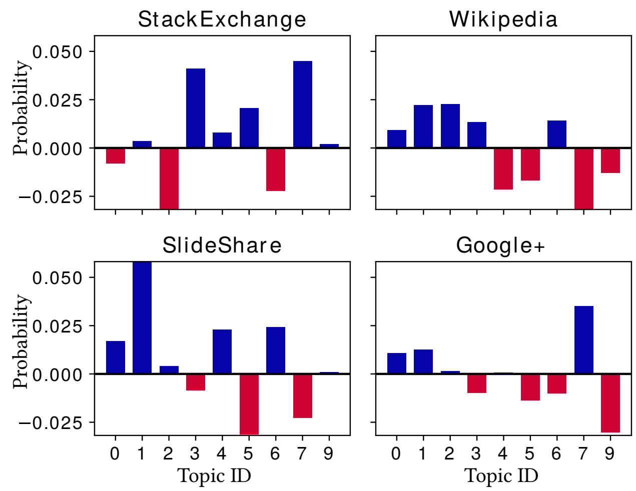
Table 1: Top-5 words for topics detected in the answers on "What are other common reasons for you to like/retweet/share/... academic research on [...] services?". The topics are interpretable and expose latent motives of researchers active on social media.

Topic 0	Topic 1	Topic 2	Topic 3	Topic 4
share	relevant	find	get	interest
peers	others	interesting	information	interesting
access	research	work	new	results
read	think	share	topic	spread
people	work	knowledge	findings	content

Topic 5	Topic 6	Topic 7	Topic 8	Topic 9
interesting	articles	research	research	make
topics	download	work	share	researchers
show	public	relevance	like	important
article	news	good	academic	work
find	available	friends	retweet	colleagues



(a) Average topic probabilities for active users



(b) Deviation from average topic probabilities for selected services

Figure 3: Analysis of topics found in user responses on the question on reasons for using social media. These topics can be interpreted as latent motives and they vary for different services. The differences in motives could explain observed variations in research experience and academic roles.

5 DISCUSSION AND CONCLUSION

In order to assess differences in demographics and usage motives between social media services, we studied survey responses of 1,731 active scholarly social media users. Our first analysis shows that **(i) the distribution of research experience and professional roles per social service varies greatly for active users**: Experienced users use social networks and services which make research results available to the general public, young researchers are more dominant in question answering services and platforms for publishing code; and **(ii) the motivation of researchers for using social media services varies per service**: While services with a higher share of inexperienced researchers may attract users who search for information, services with a high share of professors / experienced researchers attract users who want to share their research results with friends or the general public.

These findings have implications for the future development of altmetrics for scientific impact prediction: The observed variety of experience and of motivations for social media use is likely to influence the meaning of actions per service. While a post mentioning a paper on StackExchange is likely a question of a young researcher (satisfying a need for information), a post mentioning a paper on Google+ is more likely explained by an experienced researcher sharing a relevant publication with friends. This variety should be accounted for when measuring the activities of scholars in social media for scientific impact prediction, e.g. for improving literature search engines or the evaluation of research.

Altmetrics have been shown to be positively correlated with future citation counts [25, 29]. Researchers with different roles and research experience have different levels of productivity in terms of citation counts. For example, postdocs are known to have a high productivity and create more citations on average [5]. The distributions of the citation rate of users per year (which depends on their research experience and role) could be extracted from citation databases. Knowing the distribution of research experience and roles per service allows us to link these distributions with the distribution of the citation rate of users. This enables the prediction of citation counts in a probabilistic fashion using basic altmetrics (direct observations from social media) and thus for improved aggregated altmetrics scores.

Our study is mainly limited to participants from the fields of Economics and Social Sciences, most of them from Germany. In future work, we will conduct surveys to better approximate a more general distribution of research experience per service, in order to create and evaluate novel altmetrics for scientific impact prediction.

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