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Relating popularity on Twitter and Linkedin to bibliometric indicators of visibility and interconnectedness: an analysis of 8512 applied researchers in Germany

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Abstract

We analyse the degree to which the popularity of scientific authors on Twitter and LinkedIn corresponds to publication-based indicators as to their visibility and interconnectedness. Departing from the extant literature's focus on the visibility of individual papers, we turn to the popularity of individuals on social media platforms. We explore whether this popularity is reflected in the visibility that researchers achieve and the collaborations they maintain in the publication domain. Studying a large sample of applied researchers in Germany, we find congruence between researchers' popularity on social media, and both their visibility and interconnectedness in the publication domain. Comparing the effects of Twitter and LinkedIn engagement, we furthermore find that the characteristics of this relationship are associated with the intended function of the social media platform in which researchers engage. We conclude that social media platforms are a relevant channel of academic communication, alongside existing channels of formal and informal exchange.

Keywords LinkedIn · Twitter · Research dissemination · Citation impact · Altmetrics

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Introduction

Since the inception of modern science, research has developed on a twofold basis of formal communication through journals, and informal communication through preparing joint endeavours, as well as exchanging findings of common interest (Šešelja, 2020; Zollman, 2013; Entradas, 2022). With the advent of digitalisation during the twentieth and twenty-first centuries, research production has accelerated and become more inclusive (Ding et al., 2010). Yet, it remains anchored in a specific, formalised process of scientific publishing, combined with but still clearly delineated from informal exchanges on conferences, forums and seminars (Viglione, 2020; Torre, 2015; Torre & Rallet, 2005).

Social media provide a plethora of new communication channels. An increasingly broad stream of literature has emerged around the uptake of social media activities by scientists (Klar et al., 2020; Allen et al., 2013; Sugimoto et al., 2017; Ferreira et al., 2021). However, it remains under discussion as to whether social media constitutes a platform on which scientific findings can be advertised alongside other, often unrelated content (Holmberg & Thelwall, 2014; Robinson-Garcia et al., 2017), an appendix to real-world meetings (Wilkinson et al., 2015; Wen et al., 2014; Letierce et al., 2010), or a new, complementary means of academic communication in its own right—that is integrated with, yet not identical to traditional channels and fora (Shakeel et al., 2022; Kelly et al., 2016).

In an increasingly digitised society, social media play a relevant role in researchers' pursuit of increasing their visibility and interconnectedness, which can be considered prerequisites for their performance (Abbasi et al., 2011, 2012; Guan et al., 2015). Social media have a double function in helping researchers to draw attention to specific findings (Demir & Dogan, 2022; Shakeel et al., 2022; Ortega, 2016; Eysenbach, 2011), and to ascertain that their findings are more intensively cited and/or that they themselves are more often considered as collaboration partners by relevant colleagues (Klar et al., 2020; Allen et al., 2013).

To date, the extant literature has considered which groups of researchers tend to use social media (Mohammadi et al., 2018; Ortega, 2016), and for what reasons (Ke et al., 2017; Côté & Darling, 2018). Other analyses have investigated whether social media postings of new publications correlate with their subsequent citations (Eysenbach, 2011; Klar et al., 2020; Thelwall et al., 2013; Kunze et al., 2020). In contrast, the relationship between researchers' promotion of their activities on social media and their subsequent scientific visibility as individuals remains underexplored, and to date existing literature has only considered isolated aspects of it (Ortega, 2016). Some discipline-specific, small-sample studies (Shakeel et al., 2022; Patel et al., 2022; Jeong et al., 2019) have analysed correlations between researchers' social media activity and the number of citations. Empirically, however, most of them referred to articles rather than individuals as their unit of analysis. In contrast, whether the scope of the individual networks of researchers in social media is associated with broader networks in the co-publication and citation domain has not been tackled.

Furthermore, much of this existing literature has been critical as to whether a straightforward relationship between social media attention and performance actually exists (Ferreira et al., 2021). To date, various studies have suggested that the sheer extent of activity or content posted on social media is not a relevant predictor of genuine academic visibility (You, 2014; Holmberg & Thelwall, 2014; Robinson-Garcia et al., 2017). While social media use by researchers has been heralded as a revolution in scientific communication (Sugimoto et al., 2017), research on the topic has remained inconclusive. The literature on the relationship between social media posts or account characteristics and citations has not identified a clear relationship between the attention researchers receive on social media and their academic performance in terms of publication or citation counts.

We reconceptualise the link between the attention that researchers receive on social media and the attention they receive in the publication domain. We suggest that interpersonal relationships—i.e., the scope and reach of different kinds of networks—are a key analytical category. More specifically, we propose to investigate whether social media attention increases both the number of co-authors and citing authors at the level of individual researchers, asking whether those researchers who receive more attention on social media also stand out in terms of the breadth of their citation and/or co-publication networks. Accordingly, we develop the concept of followership (i.e., the number of individuals to whom one is connected) to compare visibility on social media to visibility in formal scientific communication—and to detect a possible congruence between them, as suggested by earlier research with similar ambitions (Costas et al., 2015). The conceptual notion behind this approach is that researchers use social media platforms to cultivate virtual networks that could subsequently serve as a baseline for real contacts (co-publication) or at least cognitive uptake of relevant findings (citation)—or are themselves to a degree already a reflection of individuals' prior interconnectedness on either of the traditional channels.

Our first contribution is that we focus directly on authors as units of analysis, rather than on research papers (Jeong et al., 2019; Patel et al., 2022). This enables a clear focus on the core aspect of conceptual interest: to gauge whether scientists' parallel networks in social media and formal academic communication develop in an integrated, congruent manner. More precisely, we analyse the extent to which the degree of popularity that individuals attain on social media (i.e., the number of other individuals taking note of them) corresponds with the degree of visibility they attain elsewhere (i.e., the number of individuals citing them or actively interacting with them). In addition, it allows us to better control for additional, personal-level factors which, at the level of the individual, may affect the visibility of specific researchers' outputs. As a second contribution, we expand on whether—in the publication domain—researchers receive attention as collaborators directly (co-publication), or rather through the uptake of their ideas in the scientific discourse (citation). In this regard, we document the differences between the effects of the attention that researchers receive on Twitter, a general-purpose, communication-oriented social network, and the attention that they enjoy on LinkedIn, a networking-oriented, contact-brokering site for professionals of different trades. To conduct this analysis, we focus on a unique dataset specifically compiled for this purpose, and contrast the effects found for Twitter as the most popular (and most often analysed) micro-blogging platform, and LinkedIn as a leading venue for professional online networking, on which there is far less extant research.[1] Extant research shows that there may be notable differences in "whom we 'friend' and via which platform" (Yuan & Lee, 2022), and thus the use of different platforms could be associated with scientific attention flows in various ways.

Our dataset of researchers affiliated with Fraunhofer, Europe's largest public research organisation for applied research, combines data on social media and publication activities. It tracks how many of them use Twitter and LinkedIn, and how many other accounts are part of their networks, and also includes key data on their professional profiles as published on social media. In parallel, we generated information on how many other individuals are

[1] Following initial bulk downloads, LinkedIn has either closed its APIs or limited the range of data collection operations that can be performed through them.

part of their co-publication and co-citation networks, and included further information that can be inferred from their publication record, such as scientific age.

Literature review

The role of social Media in academic communication/researchers' activity on social media networks

Communication about research is an integral part of academic activity (Klar et al., 2020; Entradas, 2022). When the Republic of Science was smaller, communication was slower and the overall public was less involved in research discourses, communication of research findings through scientific publications and communication about research were not clearly distinguished (Polanyi, 1962). This has changed for different reasons. First, the function of scientific publications has changed from a pure vehicle of communication to one relevant for performance measurement and career advances (Hynes, 1998; Wilsdon et al., 2015; Aksnes et al., 2019; Barnes, 2017). In parallel, social media as a new channel of communication has brought about new opportunities by communicating on and improving the accessibility of research results, without submitting all information to meticulous and lengthy peer review processes (Klar et al., 2020; Allen et al., 2013; Sugimoto et al., 2017; Ferreira et al., 2021). This new channel of communication speeds up the exchange of information, making it possible to reach and interact with large audiences efficiently (Côté & Darling, 2018; Loeb et al., 2014). For professionals, social media usage creates a peculiar kind of social capital that has the potential to be reflected in other dimensions of personal and professional relations (Ellison & Vitak, 2015; Ellison et al., 2007), and the scholarly use of social media has become the subject of diverse studies (Ferreira et al., 2021; Sugimoto et al., 2017). However, at the individual level, insights into the relationship between the social media popularity of researchers and their visibility in the established channels of formal academic communication networks remain rare (for an exception, see Ortega, 2016) and are far from fully explored.

Communication on social media has the potential to close the established gap between standardised academic communication and informal exchanges. First, as the rigid quality controls of peer-reviewed journals are absent, information is relayed faster and direct reactions to statements by others are possible (Côté & Darling, 2018; Loeb et al., 2014). Second, it is less ephemeral and more broadly accessible than informal exchanges. Unless withdrawn, statements remain documented and are more broadly accessible. Just as anyone is free to cite a paper, anyone can follow another person's social media accounts without it requiring a physical co-presence, such as in conferences (Torre, 2015; Torre & Rallet, 2005). Thus, social media may fill a relevant gap between formal communication and informal exchanges. Recent studies demonstrate a congruence between researchers' informal activities at conferences and the formal recognition that their research subsequently receives (Gorodnichenko et al., 2021, on publications; Leon & McQuillin, 2018, on citations; Chai & Freeman, 2019, on subsequent communication). It also seems significant that such a relationship can develop between social media popularity and established publication networks—if only because social media have been found to serve as an important 'backchannel' to informal communication at conferences (Wilkinson et al., 2015; Wen et al., 2014; Letierce et al., 2010).

Social media popularity and scientific attention

Regarding how best to capture the relevant essence of researchers' social media activity, earlier studies have suggested that, for example, the sheer amount of Twitter activity may not necessarily reflect the extent of scientific substance that is communicated, as some people communicate mechanically in high frequency (Robinson-Garcia et al., 2017) and include communication without professional relevance (Ke et al., 2017), or even actively work towards a status of social media 'celebrities' in the scientific domain, without giving primary attention to content (You, 2014). Hence, no straightforward relationship between social media attention and scientific performance could thus far be demonstrated (Ferreira et al., 2021). However, this is arguably the wrong question. The core nature and raison d'être of social networks is to provide an additional communication channel, as outlined above. This channel allows scientific findings to be relayed to a large, potentially worldwide audience and to enable exchanges regarding them. More importantly, however, it also enables researchers to establish an additional, complementary type of relationship to other scientists. For many older researchers, who joined online social networks late in their careers, this may constitute a reflection of pre-existing real-world networks, or at least of relationships that emerge in parallel to the virtual and the real-world domain (Costas et al., 2015). For most digital natives and early career researchers, it may provide an initial basis to be activated later in the real world, or translated into a first, formal communication as they start receiving citations and collaborating more broadly. For such younger individuals, formal academic visibility becomes manifest later than initial popularity in the quickly formed networks of social media relationships. In summary, existing evidence suggests that social media activity may not be considered as related to—let alone direct evidence of—performance. Instead, it is a particularly novel manifestation of researchers' interpersonal linkages. What seems worthy of inquiry, therefore, is how it relates to other, more formal types of linkages for which we have existing documentation.

Further complicating matters, academics use social networking sites for a variety of motives, and for researchers, as for social media users in general, diverse considerations are involved in "whom we 'friend' and via which platform" (Yuan & Lee, 2022). While diverse platforms have been considered as potentially relevant, two of them have been found to be of particular interest for scholarly communication on social media: Twitter and LinkedIn (Patel et al., 2022). Both are online platforms with a strong focus on social interactions, compared to other sources such as the Web of Science, Scopus, Mendeley or Academia.edu (Wouters et al., 2019).

In recent years, various empirical studies have been conducted on Twitter data, as all information on the platform remains openly accessible through application programming interfaces (APIs). Among tweeting researchers, the most prominent motive is obtaining real-time information (73%), followed by sharing information (66%) and expanding professional networks (64%). Roughly half of academics tweet to communicate on academic events and to share their research results (52% and 47%) (Mohammadi et al., 2018). Correspondingly, most tweets from academics are not only about research, but also about matters unrelated to research. This has been corroborated by qualitative analyses as well as a studies of URLs shared on Twitter (Holmberg & Thelwall, 2014; Ke et al., 2017).

In contrast, there is much less literature on academic usage of LinkedIn (Davis et al., 2020) as it is more difficult to access LinkedIn data on a large scale. Since some early incidents of bulk downloads, LinkedIn has closed most of its APIs completely or restricted the nature of queries permissible through them. Most existing studies focus on the area of talent flows (Sun et al., 2022), rather than on LinkedIn's communication dimension. However, there are indications that scientists use LinkedIn for different communication purposes than Twitter. The promotion of scientific articles, for example, seems to play a much lesser role (Thelwall et al., 2013). A study of referral data of 110 scientific articles found that more than half of the social referrals came from Twitter, whereas LinkedIn was counted towards a category "other", which made up less than 4% of referrals (Wang et al., 2016). In line with Yuan and Lee (2022), we tentatively conclude that "different considerations are involved in whom [researchers] befriend via LinkedIn than via Twitter". Hence, the two networks in which they thus become embedded will not necessarily be the same—nor can it be expected for their connection to traditional networks of scientific communication.

Finally, a caveat needs to be made with a view to the still skewed distribution of social media usage across countries and academic fields. There is much variation in the activity of researchers on social networks. A recent study of around 300,000 Twitter accounts, linked to authors from the Web of Science, found that researchers affiliated with US or UK institutions are overly represented (40%), and that the relative share of Twitter users is highest in biomedical and health sciences, whereas the absolute share of researchers from social sciences and humanities are the highest (Costas et al., 2020). Moreover, the distribution of activity among Twitter users is highly skewed, as only a few researchers issue the majority of tweets (Yu et al., 2019). Accordingly, studies focusing on the congruence between researchers' networks in the domain of scientific publication, and their corresponding networks in social media, should limit these additional and diverse sources, and adjust the equivalent of both country and disciplinary perspectives to the highest degree possible.

Hypotheses

This paper asks whether the interconnectedness of researchers on social media is associated with more interconnectedness in their collaboration and citation networks. Existing literature shows that researchers turn to social media to expand their social and their professional networks, to communicate on research and consequently to increase their popularity or visibility (Mohammadi et al., 2018). However, the concrete empirical relationship between the attention received on social media and the attention received through citations on research papers has not been established (Ferreira et al., 2021). While we follow Costas et al. (2015) in establishing a correlation between the altmetric scores and citations of individual researchers, we will focus on the breadth or scope of networks, rather than on the extent of activities. More precisely, we relate the number of individuals' contacts on social media to the number of links in the traditional domain of scientific communication. To avoid the noise created by 'social media hyperactivity', we focus on received linkages, i.e., the notion of social media popularity rather than social media activity. Our perspective on the traditional domain of scientific communication will therefore include collaborations and citations. Our study focuses on associations rather than causal relationships, as we do not explicitly account for the time dimension. Yet, our approach allows us to consider whether social media attention for researchers and the breadth of their collaboration and citation networks are correlated.

More extensive social media connections may enable individuals to find more collaborators. Individuals connected on social media are more likely to collaborate, since they have interacted before: Earlier research has shown that much research collaboration originates in informal exchanges (Bozeman & Corley, 2004), and social media provide another channel for such exchanges. More extensive social media connections may also lead to individuals receiving citations from more distinct authors: Researchers may be inclined to cite the works of members of their networks more frequently, because of their social connectedness and because they become more directly aware of new research outputs produced by members of their networks. This expectation can be based on a social constructivist understanding of citation behaviour (Bornmann & Daniel, 2008), as well as on a potential analogy to the role of informal exchanges at academic conferences for citation (Leon & McQuillin, 2018). Hence, we hypothesise:

Hypothesis (1a) Researchers who are more popular on social media have more distinct co-authors.

Hypothesis: (1b) (1b) Researchers who are more popular on social media also receive more citations

(from different individuals, since networks are between individuals).

With a view to LinkedIn being a professional network platform rather than primarily a communication-oriented platform, we assume that LinkedIn popularity is more strongly associated with collaboration and more weakly associated with scientific attention. Scientific attention, in turn, could be found to be more closely associated with Twitter popularity. Hence, we hypothesise:

Hypothesis: (2) Compared to Twitter popularity, we expect LinkedIn popularity to be more strongly associated with the number of distinct co-authors than with the number of distinct citing authors.

Data and methods

Dataset

Our unique *population dataset* was generated by linking data on Twitter and LinkedIn accounts to employee data from Fraunhofer-Gesellschaft. Fraunhofer is Europe's largest public research organisation for applied research, comprising more than 70 institutes employing around 29,000 researchers. Fraunhofer is key to the German innovation system, mostly conducting research in the areas of engineering, computer science and life sciences, with the objective of developing innovative technologies and products of commercial value. Linking the spheres of research and business, Fraunhofer institutes play an important role in the German innovation system.

We constructed a dataset of the publications and conference proceedings of Fraunhofer researchers from the year 2000, based on publications in Elsevier's Scopus. We aggregated this information at the level of individual researchers, taking into consideration all researchers who have a Fraunhofer affiliation according to at least one of their publications in Scopus. Scopus might be biased towards natural sciences, biomedical research and engineering, and provide less reliable data on social science, the arts and humanities (Mongeon & Paul-Hus, 2016; Vera-Baceta et al., 2019). However, this bias is of limited relevance in the Fraunhofer context. All data was retrieved from the Scopus 2021 version, and only researchers with at least one publication between 2017 and 2021 were included in the dataset, so as to exclude individuals who have retired or changed career paths from the analysis. We then extended this dataset with Twitter and LinkedIn data. To scrape Twitter data, we used the *rtweet package* for R (Kearney, 2019). The first matching of names from a Fraunhofer employee list with the names of Twitter accounts resulted in a high number of false positive matches that invalidated our sample. Hence, we modified our approach and took Fraunhofer institutes with an official Twitter account as our starting point ($n = 68$). We then narrowed our search space by collecting basic information on the followers of these institutes. Retaining only accounts with a name match following a Fraunhofer institute on Twitter, we excluded almost all false positives, as confirmed by manual checks. We also confirmed that no accounts known to us were excluded by restricting the sample to followers of Fraunhofer institutes. In addition, this restriction ensured that those users who were analysed, use their Twitter accounts partly for work-related purposes, as they follow their employer. All data was downloaded from Twitter in early 2022.

In parallel, we collected LinkedIn data on the activity of Fraunhofer researchers using a tool for automated data collection. We provided a list of all Fraunhofer institutes as input. The tool identified the LinkedIn accounts of these institutes and extracted public information from the accounts of LinkedIn users, indicating these institutes as their workplace. To obtain detailed information on these accounts, direct access to an account with at least a third-degree connection to them was necessary. To alleviate possible biases resulting from this restriction, we used several individual user accounts as anchor points for the data collection.

Next, we merged the datasets, i.e., bibliometric data, Twitter and Linked data, using a string-matching algorithm for author-names.[2] To exclude homonyms, we followed four steps: (i) exact matches were included; (ii) matches with a similarity score above 0.9 were manually validated; (iii) to further validate all matches, cross-checking the Scopus list against an internal employee list; (iv) manual validation of a random subset of observations to ensure that there were no systemic biases. Not all Fraunhofer researchers listed in Scopus have accounts on Twitter or LinkedIn. For such researchers, the variables derived from Twitter and LinkedIn take the value of zero.

Measures

Dependent variables

Our dependent variables characterise the social connectedness of Fraunhofer researchers from a bibliometric perspective. The first was the stock of distinct citing authors, and the second was the stock of co-authors. We obtained the values for these variables by aggregating, across the publications of each individual author, all authors appearing as their co-authors or citing authors, and then counting the number of their unique co-authors and

[2] We used the Levenshtein distance to measure the similarity of text-strings. Text data was cleaned first by setting all characters to lower case and removing special characters and punctuation.

citing authors. In doing so, we used author IDs assigned by Scopus rather than author names, enabling us to disambiguate between different authors of the same name.

Independent variables

Two variables measuring the count of followers on Twitter and LinkedIn served as our independent variables. Both these variables measured the popularity of Fraunhofer researchers in the respective social networks. On Twitter, users normally customise their feeds by following other accounts that are of interest to them. On LinkedIn, users tend to connect with each other rather than follow each other. When connected, users automatically follow each other. However, it is also possible to follow other users rather than connect with them. Therefore, the follower numbers measure popularity on LinkedIn and on Twitter.

Control variables

We added a battery of control variables on the characteristics of Twitter and LinkedIn accounts. We included these variables to ensure that we obtained a clear picture of the comparisons between LinkedIn and Twitter popularity, as measured by follower numbers and our dependent variables. We ruled out that these comparisons are conflated merely by engagement on Twitter by including, as controls, the counting of tweets and retweets posted by users, and the number of accounts that they follow. We also controlled for the number of public lists that users are on. These lists are created by Twitter users and displayed in a feed the tweets from the accounts included in the list. Hence, they provided an important complement to the number of followers as a measure of Twitter popularity.

Regarding LinkedIn, we accounted for the number of endorsements that users received from others for specific skills and for being agreeable co-workers. Thereby, we ensured that our models allowed differentiation between the effects of LinkedIn popularity in terms of followers, and the effects of individual characteristics relevant in a professional context as reported to LinkedIn. Moreover, we obtained information from LinkedIn on whether users report holding a PhD. While all Fraunhofer researchers can be assumed to have a higher education degree, not all of them have a PhD. Hence, we included this variable to avoid conflating differences in university education levels and LinkedIn popularity when studying possible explanations of changes in the dependent variables.

We included additional variables to account for additional author characteristics. We controlled for the total number of articles published and for the total number of citations received. We also included a dummy for female gender that may—empirically—(negatively) correlate with popularity (Zhu et al., 2019). We added scientific age, i.e., calculated based on the time passed since the year of an author's first publication in Scopus, as a proxy for seniority. We also controlled for disciplinary affiliations with dummy variables for the most frequent All Science Journal Classification (ASJC) codes in researchers' publication stocks since, according to prior literature, social network use could vary by discipline (Mohammadi et al., 2018). Table 1 lists the variables used in the analysis.

Estimation approach

We used negative binomial regression models because we modelled dependent count variables that are over-dispersed, i.e., their variance is higher than their mean (Long & Freese,

Table 1 Variables used in the analysis

Variable	Type	Description	Source
distinct_co-authors	Dependent variables	Number of an author's distinct co-authors	Scopus
distinct_citing_authors		Number of an author's distinct citing authors	
tw_followers_count	Main explanatory variables	Number of an author's followers on Twitter	Twitter
li_followers_count		Number of an author's followers on LinkedIn	LinkedIn
tw_following_count	Control variables	Number of accounts an author follows on Twitter	Twitter
tw_listed_count		Number of public lists that an author is included in on Twitter	
tw_favourites_count		Number of tweets an author has marked as 'favourite'	
tw_statuses_count		Number of an author's tweets and retweets	
li_phd		Binary variable indicating whether an author holds a PhD/doctorate degree	LinkedIn
li_skill_count		Number of professional skills of an author	
li_reco_count		Number of personal recommendations that an author has received	
articles_published		Number of articles an author has published (Scopus publication types *article, letter, review* and *note* considered)	Scopus
scientific_age		Time passed since an author's first publication, counted in years (Scopus publication types *article, letter, review* and *note* considered)	
female		Binary variable identifying an author's female gender	

Table 2 Descriptive statistics

	Min	Mean	Median	Max
distinct_co-authors	0	22	11	1454
distinct_citing_authors	0	700.77	66	66542
tw_followers_count	0	0.01	0	7.96
li_followers_count	0	0.06	0	5.08
tw_following_count	0	0.02	0	5
tw_listed_count	0	0	0	0,49
tw_favourites_count	0	0.11	0	168.13
tw_statuses_count	0	0.12	0	455.51
li_phd (d)	0	0.07	0	1
li_skill_count	0	1.77	0	50
li_reco_count	0	0.01	0	2
articles_published	0	11.37	3	741
scientific_age	0	9.82	8	24
female (d)	0	0.18	0	1

The variables tw_followers_count, li_followers_count, tw_following_count, tw_listed_count, tw_favourites_count and tw_statuses_count were divided by 1000 prior to the analysis

d dummy

2006). As our descriptive analysis shows, one of our dependent variables, namely the number of distinct citing authors, contains many zeros. However, we do not consider this variable to be zero-inflated, as its zeros result from the same data-generating process as the other values of this variable. Whether any of the publications on which our dataset is based receive zero, one or many citations from different authors depends on the same factors.

Prior to estimating our models, we standardised all explanatory variables by computing their z-scores so that for each variable, the mean takes on the value of zero and the standard deviation takes on the value of one. This procedure accommodates the fact that one-unit changes are more common in some variables than others, depending on their overall variance, and reduce the impact of extreme outliers on the estimates. Thus, the marginal effects of changes in each independent variable on changes in the dependent variable become directly comparable, enabling a tentative assessment of which variable has a stronger impact (Afifi et al, 2011).

A disadvantage of models based on standardised variables is that the resulting marginal effects are difficult to translate into a concrete relationship between dependent and explanatory variables. Therefore, we provide additional models with non-standardised independent variables in the Appendix. Here, we divided the variables with follower counts from Twitter and LinkedIn by 1000 prior to estimation, as the effect of one additional follower on the dependent variable might well be negligible, whereas an increase in the order of magnitude could have a relevant effect. In these models, the marginal effect of 1000 additional followers on the respective dependent variables can be directly read from the coefficients.

Table 3 Pearson correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. distinct_co-authors													
1. distinct_citing_authors	0.51*												
3. tw_followers_count	0.04*	0.06*											
4. li_followers_count	0.05*	−0,01	0.05*										
5. tw_following_count	0,02	0,01	0.72*	0.06*									
6. tw_listed_count	0,02	0,02	0.73*	0,02	0.56*								
7. tw_favourites_count	0,01	0,00	0.34*	0,00	0.47*	0.25*							
8. tw_statuses_count	0,00	0,00	0.35*	0,01	0.42*	0.51*	0.32*						
9. li_phd	0.04*	0,00	0,02	0.47*	0,02	0,01	0,00	0,00					
10. li_skill_count	0,01	−0,03	0.04*	0.56*	0.03*	0,01	0,00	0,00	0.51*				
11. li_reco_count	0,01	−0,01	0.03*	0.28*	0,02	0,01	0,00	0,02	0.17*	0.24*			
12. articles_published	0.54*	0.82*	0.03*	0,01	0,00	0,01	0,01	0,00	0,02	−0,03	0,00		
13. scientific_age	0.25*	0.36*	0,01	0.06*	−0,01	−0,01	0,00	−0,01	0.09*	0,02	0.03*	0.45*	
14. female	−0.03*	−0.03*	−0,02	−0.04*	−0,03	−0,01	−0,02	−0,01	−0.04*	−0.06*	−0,03	−0.06*	−0.12*

*$p < 0.1$

Table 4 Regression models

Variables	(1a) distinct_co authors	(1b) distinct_citing_authors	(2a) distinct_co authors	(2b) distinct_citing_ authors	(3a) distinct_coauthors	(3b) distinct_citing_authors
Twitter popularity						
tw_followers_count	0.0409**	0.0908**			0.0367**	0.0845**
	(0.0180)	(0.0409)			(0.0175)	(0.0415)
Linkedin popularity						
li_followers_count			0.0917***	0.0224	0.0909***	0.0198
			(0.0147)	(0.0254)	(0.0147)	(0.0254)
tw following_count	0.00358	−0.0156			−0.000846	−0.0153
	(0.0156)	(0.0250)			(0.0151)	(0.0249)
tw_listed_count	0.00488	0.0390			0.00871	0.0437
	(0.0170)	(0.0373)			(0.0174)	(0.0399)
tw_statuses_count	−0.0297**	−0.0417*			−0.0302**	−0.0431*
	(0.0127)	(0.0226)			(0.0125)	(0.0226)
tw_favourites_count	−0.00337	−0.0404**			−0.000339	−0.0395**
	(0.0106)	(0.0191)			(0.0105)	(0.0191)
li_skill_count			−0.0191	−0.0730***	−0.0196	−0.0712***
			(0.0122)	(0.0237)	(0.0122)	(0.0236)
li_reco_count			−0.00916	0.0372*	−0.00964	0.0363*
			(0.00964)	(0.0196)	(0.00966)	(0.0196)
phd			0.0590***	0.0787***	0.0595***	0.0816***
			(0.0116)	(0.0234)	(0.0116)	(0.0233)
articles_published	0.572***	0.964***	0.573***	0.996***	0.568***	0.954***
	(0.0193)	(0.0527)	(0.0191)	(0.0526)	(0.0191)	(0.0526)
scientific_age	0.148***	1.006***	0.136***	0.991***	0.136***	1.001***
	(0.0124)	(0.0288)	(0.0123)	(0.0289)	(0.0123)	(0.0289)

Table 4 (continued)

Variables	(1a) distinct_co authors	(1b) distinct_citing_authors	(2a) distinct_co authors	(2b) distinct_citing_ authors	(3a) distinct_coauthors	(3b) distinct_citing_authors
Female	−0.0547***	−0.0111	−0.0527***	−0.0133	−0.0525***	−0.0119
	(0.0102)	(0.0198)	(0.0101)	(0.0199)	(0.0101)	(0.0198)
Constant	2.835***	5.106***	2.829***	5.107***	2.828***	5.102***
	(0.00955)	(0.0186)	(0.00949)	(0.0186)	(0.00948)	(0.0186)
Res. Field Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8512	8512	8512	8512	8512	8512
Pseudo-R2	0.0656	0.0581	0.0676	0.0580	0.0678	0.0583

Standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

All explanatory variables are standardised

Results

Descriptive analysis

As Table 2 shows, our explanatory variables for Twitter as well as LinkedIn usage contain many zeros, since many of the Fraunhofer researchers included in our sample do not use these social networks at all. The distribution of the numbers of distinct co-authors and distinct citing authors are highly skewed, indicating that many researchers only have a low number of publications in Scopus. This is not surprising as, compared to universities, scientific publications are a less relevant parameter for career success at Fraunhofer, where researchers conduct contract research for the industry and public institutions. While the vast majority of authors have at least one co-author (only 38 do not), many researchers have not collected any citations. The correlation analysis in Table 3 shows that the numbers of distinct co-authors and distinct citing authors are moderately correlated (0.51), and their correlation is significant at the 5% level. The correlation coefficient between follower counts on Twitter and LinkedIn is very low (0.06) and significant at the 5% level. Unsurprisingly, correlation coefficients are mostly significant and relatively high among both Twitter and LinkedIn variables.

Regression models

Table 4 gives the results of the regression models. All explanatory variables are standardised using their z-score. We estimate three series of models with our two dependent variables. The first series includes Twitter and bibliometric indicators, the second includes LinkedIn and bibliometric indicators, and the third includes all variables. The signs and significance of the coefficients are consistent across the three series. The McFadden pseudo-R-squared values range between about 0.06 and 0.07. These values are useful for comparing the fit of different models using the same dataset to predict the same outcomes. If these values appear relatively low from a general perspective, this does not as such indicate that the models would not identify significant associations between the variables included in the models. The pseudo-R-squared values are highest for the third series including all variables, indicating better model fit. Therefore, we focus our comments on the third series.

In Models 3a and 3b, Twitter popularity is significantly and positively associated with both the numbers of distinct co-authors and distinct citing authors. LinkedIn popularity is significantly and positively associated with the number of distinct co-authors. These results indicate that popularity in social networks and the size of professional networks, as well as the visibility of publications in the academic sphere, are positively associated with one another. Comparing the effects of the main explanatory variables, increases in the number of distinct co-authors are stronger for the follower count on LinkedIn than on Twitter. For increases in the number of distinct citing authors, only the followers on Twitter matter.

Regarding the controls, significant negative correlations between Twitter activity (statuses_count and favourites_count) are slightly surprising: Researchers spending a great deal of time producing and interacting with Twitter content appear to have smaller networks with a view to co-authors, and are cited by a fewer number of authors. In short, while being popular on Twitter has positive implications for academic success, intense Twitter use does not, and might even be counterproductive. Further, the stock of articles published and the scientific age are positively associated with both the numbers of distinct co-authors and distinct citing authors. This was to be expected, since higher publication outputs and academic seniority are close to the mathematical preconditions for having a higher number of distinct co-authors or getting more citations. Furthermore, our findings for gender resonate with the established concern that female researchers have smaller networks.

Another credible finding is that researchers who indicate that they hold a PhD degree on LinkedIn have more distinct co-authors and distinct citing authors. While we control for the stock of publications, those with PhD degrees (or those making a point of having one) can still expect to be embedded more broadly in the academic domain than others. In contrast, the number of skills listed on a LinkedIn account is significantly and negatively associated with the number of distinct citing authors. While this is not immediately intuitive, it still resonates with the notion that those with the clearest profile may develop the broadest networks in academia. Finally, we find that higher numbers of LinkedIn recommendations are positively associated with the number of distinct citing authors. Thus, there is once again congruence between the breadth of attention in social media and the breadth of attention in traditional scientific communication.

Given that our models use z-standardised independent variables, the coefficients provide indications of relative effect sizes. The significant coefficients of our main explanatory variables are between about 0.04 and about 0.08. The coefficients of most other explanatory and control variables are in a similar order of magnitude. Only the baseline effects for the number of articles already published and scientific age are notably higher. However, that the association between our dependent variables and these fundamental determinants of scientific visibility somewhat eclipses those with other factors does not render the search for other *ceteris paribus* effects invalid. After all, the ambition of this paper is not to assert that social media presence was the predominant determinant of formal scientific visibility—which it is obviously not—but to explore if it could have developed an additional effect under otherwise equal conditions.

With a view to concrete marginal effects, Table 5 in the Appendix presents the results of estimated regression models based on non-standardised explanatory variables. Instead, for these models, key variables from LinkedIn and Twitter have been divided by 1000 to account for differences in the order of magnitude of social media popularity. On this basis, we find that a concrete increase of 1000 Twitter followers is associated with an increase of 0.20 in the number of distinct co-authors and of 0.45 in the number of distinct citing authors. An increase of 1000 LinkedIn followers is associated with an increase of 0.41 in the number of distinct co-authors. Admittedly, the effect of social media visibility is thus somewhat limited, and it can be concluded that a substantive social media audience would be required to effect a significant change in the patterns of formal scientific collaboration.

Discussion

We have analysed how the popularity of researchers on Twitter and LinkedIn relates to scientific networks and attention received in the domain of academic publications (as measured through the number of their distinct co-authors and distinct authors citing their publications). Using a dataset covering all Fraunhofer researchers listed in Scopus, we find that there is congruence between social media activity and traditional scientific communication, even when controlling for a number of factors that earlier literature has found to otherwise influence researchers' scientific networks (Mohammadi et al., 2018; Ke et al., 2017; Côté & Darling, 2018).

As one central finding, we can confirm that *researchers who are more popular on social media have more distinct co-authors* (Hypothesis 1a). Researchers receiving more attention on social networking sites have a slight advantage regarding the search for co-authors and the visibility of their publications, at least when their popularity changes in the order of magnitude. This suggests that, on occasion, boosting their social media popularity could enable some researchers to find an additional new co-author or moderately increase their number of distinct citing authors. A possible explanation is that individuals following them on social networks have a higher collaboration readiness and are more likely to take note of their publications (Klar et al., 2020; Allen et al., 2013), as attention from academic peers is scarce and a contested resource (Franck, 2002). However, as effect sizes are moderate, our results indicate that increasing researchers' social media popularity to extend their formal academic network would be a hard, if not an outright futile undertaking in most cases.

We can only partially confirm that *researchers more popular on social media also receive more citations (from different individuals, since networks are between individuals)* (Hypothesis 1b). Popularity on Twitter, designed for acclamation and communication, is significantly associated with both more co-authors and more citing authors, with a higher correlation coefficient for the second. But popularity on LinkedIn, designed to trigger and facilitate collaboration, only correlates with more co-authors. To fully understand how social media popularity relates to bibliometric indicators, further studies might be necessary, to account in more detail for the specific characteristics of different social networks. Moreover, the limited size of the concrete marginal effects identified in the models suggest that a mechanism, by which researchers become aware of yet-to-be-cited literature primarily on social media is only now, if at all, emerging. A tentative interpretation is that the parallel development of online platforms for literature searches prevents such a functional shift.

With a view to the role of LinkedIn, we can confirm that *compared to Twitter popularity, we expect LinkedIn popularity to be more strongly associated with the number of distinct co-authors than with the number of distinct citing authors* (Hypothesis 2), at least when compared to Twitter popularity. We find that the associations we observed seem to reflect the intended main purpose of the specific social network, and confirm this hypothesis. Popularity on Twitter, designed for acclamation and communication, is significantly associated with both more co-authors and more citing authors, with a higher correlation coefficient for the latter. Popularity on LinkedIn, which is geared more towards professional networking, only correlates with more co-authors. A possible explanation for these associations can be found in earlier literature, pointing to differences in the academic usage of social networks (Wouters et al., 2019), and highlighting the fact that how individuals establish networks on social media platforms depends on the nature and purpose of these platforms (Yuan & Lee, 2022).

Moreover, we observe that authors tend to have more followers on Twitter than on LinkedIn. This could explain why Twitter popularity is a more effective vehicle to draw attention to study results, which may then translate into academic attention (as measured by citations from distinct authors). It could also explain why increases in the number of LinkedIn followers have higher marginal effects on the number of distinct co-authors than increases in the number of Twitter followers. A reason for the difference in follower numbers could be that by default, Twitter users start following the accounts of other users unilaterally. In contrast, on LinkedIn, the default is that users connect to others by establishing *bi*directional connections that must be reconfirmed by the other party in a process similar to establishing contact and signalling shared interests in the real world. Users connected in such a fashion then automatically become each other's followers (However, it is also possible to follow other accounts *uni*directionally on LinkedIn).

Finally, in contrast to the social media popularity of researchers, their active social media engagement seems to matter less or even be counterproductive. Hence, our findings remain in line with previous suggestions that the extent of sheer activity in social networks follows its own logic (You, 2014; Holmberg & Thelwall, 2014; Robinson-Garcia et al., 2017), and no direct connections can be made with researchers' interconnectedness in the traditional domains of academic communication. This adds to the previous literature that has not found substantial links between social network activity and bibliometric performance indicators (Ferreira et al., 2021). Hence, we confirm that the straightforward use of social media activity as a performance 'altmetric' may be highly problematic (You, 2014; Holmberg & Thelwall, 2014; Robinson-Garcia et al., 2017). In combination with our main findings, this underlines a surprising contrast between (passive) social media popularity and the sheer extent of social media activity, with the latter not only lacking any positive effects on bibliometric networks but at times even displaying a negative effect. This underlines that researchers' social media activity alone may not be effective for improving scientific networks.

Conclusion

How does social media complement more established ways of academic communication, resting on a combination of scientific publications and informal meetings? Studying a population sample from Germany's largest public applied research organisation, Fraunhofer, we find that social media provides a relevant additional vehicle of academic communication, at least for some researchers. Other than in traditional journals, content on social media is not quality-tested and hence cannot be considered scientifically substantive knowledge output. Instead, social media are primarily designed to raise attention and increase individuals' visibility and popularity. This is more akin to more long-standing forms of informal communication that precede and accompany formal scientific collaboration. The attention and breadth of popularity that researchers from the pre-social media era would have had to establish through regular conference visits and bilateral calls can today be partially obtained through activities on social media. Hence, it is logical to see that the congruence of the latter type of activities, with co-authorship and citation scores that have in multiple ways been empirically demonstrated, appear to also be present for social media engagement (Chai & Freeman, 2019; Gorodnichenko et al., 2021; Leon & McQuillin, 2018).

Our findings support the notion that social media have become a new part-alternative, part-additional communication channel in, of and about science that integrates with existing ones, as some of the more recent literature has suggested (Shakeel et al., 2022; Kelly et al., 2016; Costas, 2015). However, while our findings point to the relevance of social media popularity, they do not support the idea that the extent of social media activity could be a measure of scientific performance. The absent or even negative relationship between social media activity and a broadening of meaningful collaboration (co-authorship) or uptake of results (citations) indicates that the idea of 'the more, the better' cannot be sensibly applied in this context.

A limitation of our analysis is that the explanatory variables in our models only explain a small part of the variation in the bibliometric indicators used, i.e., the pseudo-R-squared values of our models are rather low. This indicates that the associations observed between Twitter and LinkedIn popularity on the one hand and bibliometric indicators on the other could turn out to be different in samples with different characteristics than our population sample. In addition, it indicates that our variables alone are not the only factors to explain co-authorship. Yet, the significant coefficients of our variables demonstrate that our models have at least some explanatory power.

Further research could explore the surprising contrast between the positive associations of social media popularity and bibliometric indicators on the one hand, and the negative associations of social media activity and such indicators on the other. This contrast could indicate that researchers have more success in acquiring co-authors and earning citations when they have social media accounts, but hardly use them. However, it could also indicate that fully understanding the effects of academic social media popularity requires consideration of factors not included in the present analysis.

Related to this, the lack of a full-fledged time dimension in both LinkedIn and Twitter data has limited our ability to control for reverse causal effects. Typically, researchers entering social media at a time when they already enjoy broad popularity in the informal and the publication domain will immediately attract many followers, rather than vice-versa. To identify the causal effects of social media popularity and distinguish them from other more fundamental ones, further research could seek to establish complete panel datasets so that the time dimension could be considered. This would allow us to turn to the causal effects of social media popularity on the attention researchers receive in the domain of scientific communication.

Appendix

See Table 5.

Table 5 Regression models (robustness check)

Variables	(1a) distinct_coauthors	(1b) distinct_citing_authors	(2a) distinct_coauthors	(2b) distinct_citing_authors	(3a) distinct_coauthors	(3b) distinct_citing_authors
Twitter popularity						
tw_followers_count	0.218**	0.485**			0.196**	0.452**
	(0.0960)	(0.219)			(0.0936)	(0.222)
Linkedin popularity						
li_followers_count			0.416***	0.102	0.412***	0.0897
			(0.0668)	(0.115)	(0.0667)	(0.115)
tw following_count	0.0180	−0.0785			−0.00424	−0.0768
	(0.0783)	(0.126)			(0.0757)	(0.125)
tw_listed_count	0.518	4.131			0.924	4.632
	(1.805)	(3.952)			(1.846)	(4.233)
tw_statuses_count	−0.00569**	−0.00798*			−0.00578**	−0.00824*
	(0.00243)	(0.00432)			(0.00239)	(0.00432)
tw_favourites_count	−0.00138	−0.0165**			−0.000139	−0.0162**
	(0.00434)	(0.00785)			(0.00431)	(0.00782)
li_skill_count			−0.00328	−0.0125***	−0.00335	−0.0122***
			(0.00209)	(0.00406)	(0.00209)	(0.00405)
li_reco_count			−0.0851	0.346*	−0.0896	0.337*
			(0.0896)	(0.182)	(0.0898)	(0.182)
phd			0.231***	0.307***	0.232***	0.319***
			(0.0454)	(0.0913)	(0.0453)	(0.0911)
articles_published	0.0191***	0.0322***	0.0191***	0.0333***	0.0190***	0.0319***
	(0.000645)	(0.00176)	(0.000638)	(0.00176)	(0.000637)	(0.00176)
scientific_age	0.0215***	0.147***	0.0198***	0.144***	0.0198***	0.146***
	(0.00181)	(0.00420)	(0.00180)	(0.00421)	(0.00180)	(0.00421)
Female	−0.141***	−0.0286	−0.136***	−0.0343	−0.135***	−0.0306

Table 5 (continued)

Variables	(1a) distinct_coauthors	(1b) distinct_citing_authors	(2a) distinct_coauthors	(2b) distinct_citing_authors	(3a) distinct_coauthors	(3b) distinct_citing_authors
	(0.0262)	(0.0511)	(0.0260)	(0.0512)	(0.0260)	(0.0511)
Constant	4.602***	2.129	4.657***	2.137	4.674***	2.152
	(1.158)	(2.359)	(1.152)	(2.361)	(1.151)	(2.357)
Res. Field Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8512	8512	8512	8512	8512	8512
Pseudo-R2	0.0656	0.0581	0.0676	0.0580	0.0678	0.0583

Standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Explanatory variables are not standardised. The variables tw_followers_count, li_followers_count, tw_following_count, tw_listed_count, tw_favourites_count and tw_statuses_count were divided by 1000 prior to the analysis

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