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RESEARCH ARTICLE

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"Heterogeneous couplings": Operationalizing network perspectives to study science-society interactions through social media metrics

Rodrigo Costas[1,2] | **Sarah de Rijcke**[1] | **Noortje Marres**[1,3]

[1]Centre for Science and Technology Studies (CWTS), Leiden University, Leiden, The Netherlands

[2]DST-NRF Centre of Excellence in Scientometrics and Science, Technology and Innovation Policy, Stellenbosch University, Stellenbosch, South Africa

[3]Centre for Interdisciplinary Methodologies, University of Warwick, Coventry, UK

Correspondence

Rodrigo Costas, Centre for Science and Technology Studies (CWTS), Leiden University, Leiden, The Netherlands.
Email: rcostas@cwts.leidenuniv.nl

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Abstract

Social media metrics have a genuine networked nature, reflecting the networking characteristics of the social media platform from where they are derived. This networked nature has been relatively less explored in the literature on altmetrics, although new network-level approaches are starting to appear. A general conceptualization of the role of social media networks in science communication, and particularly of social media as a specific type of interface between science and society, is still missing. The aim of this paper is to provide a conceptual framework for appraising interactions between science and society in multiple directions, in what we call heterogeneous couplings. Heterogeneous couplings are conceptualized as the co-occurrence of science and non-science objects, actors, and interactions in online media environments. This conceptualization provides a common framework to study the interactions between science and non-science actors as captured via online and social media platforms. The conceptualization of heterogeneous couplings opens wider opportunities for the development of network applications and analyses of the interactions between societal and scholarly entities in social media environments, paving the way toward more advanced forms of altmetrics, social (media) studies of science, and the conceptualization and operationalization of more advanced science-society studies.

1 | INTRODUCTION

"Altmetrics" and more specifically social media metrics have a genuine networked nature (Haustein, Bowman, & Costas, 2016). This essentially means that these metrics capture and reflect the networking characteristics of the social media platform from where they are derived. However, this networked nature has been relatively less explored in the literature on altmetrics and scholarly communications, although new network-level approaches are starting to appear. Recent work on the analysis of *communities of attention* (Haustein, Bowman, & Costas, 2015), Twitter-based disciplinary *social media communities* (Said et al., 2019), the *follower/followee relationships* of scholarly authors on Twitter (Robinson-García, Van Leeuwen, & Rafols,), the *co-saved* and *co-tweet* linkages of scientific publications (Didegah & Thelwall, 2018), *tweet coupling* (Hassan et al., 2020) or the proposal of *co-readership* (Kraker, Schlögl, Jack, & Lindstaedt, 2015), and *readership coupling* (Haunschild & Bornmann, 2015a) on Mendeley, are good examples of this new networked dimension in altmetrics research. However, a general conceptualization of the role of social media networks in science communication, and particularly of social media as a specific type of interface between science and society, is still missing. The aim of this paper is to provide a first conceptual systematic discussion on this point. We argue that the role of social media platforms in the "formatting" and curation of engagement between science and society needs to be more proactively taken into account in the development of social media metrics (Marres, 2015). In social media, a variety of actors, including scientists, journalists, policy-makers, activists, marketing professionals, and public commentators participate in science communication, and platform metrics orient communication toward specific ideals of spread-ability and influence gained through networking (Fourcade & Healy, 2017; Gerlitz & Lury, 2014) something which (Gerlitz & Lury, 2014) refer to as the "reactivity of social media measures".

Our particular concern in this paper is with the consequences of the use of social media analytics in the evaluation of science. In particular, we are concerned that the growing reliance on altmetrics as indicators of the societal relevance and public reach of science has wider implications for how the science-society interface is envisioned and configured: social media-based measures of influence and impact risk to re-instate a one-directional, non-interactive conception of the relation between science and society, whereby the focus is on the degree to which influence, impact, and communications by the former are received by the latter. Such a uni-directional conception of public outreach and societal relevance of science stands in sharp contrast to the relational and interactive visions of engagement *between* scientific and social actors, which digital media were once believed to make possible (Davies & Hara, 2017). In addition, the influence of the structure of social media platforms themselves are often ignored, while the ground level of social media interaction design and measurement significantly shapes how forms of user response and activity (e.g., likes, retweets, comments, replies, etc.) are elicited.

Our paper seeks to demonstrate how a relational framework for appraising science-society engagement—one which values interactions between science and society in multiple directions—can be developed in social media analysis, which we call *heterogeneous couplings*.

The concept of heterogeneous couplings is informed by a wider methodological commitment in the sociology of science to deploy network approaches in large-scale data analysis to surface less obvious instances and forms of science-society interaction that leave their trace in public records like social media (Callon, 2006; Marres & Gerlitz, 2016). In the context of altmetric research, the conceptualization of heterogeneous couplings should enable a broadening of the range of interactions between scientific and societal actors online, which are not per se restricted to objects with DOIs or URLs (e.g., papers or research products), but may include different kinds of objects (other types of URLs), interactions, and social media acts (mentions, tags, and so on) (Haustein et al., 2016). The framing of the objects of analysis that we put forward in this paper is deliberately broad, and comprises not only scholarly actors (e.g., scientific institutions, researchers, journals, etc.), their scholarly activities (e.g., conferences, collaborations, funding, etc.), outputs (e.g., publications, datasets, conferences, etc.), and their epistemic features (e.g., disciplines, topics, research lines, schools of thought, etc.), but also societal actors (e.g., Non-governmental organizations (NGOs), non-academic associations, journalists, political parties, social movements, citizens, etc.), their activities (e.g., campaigns, information strategies, awareness creation, etc.), and their epistemic features (e.g., transformative agenda's knowledge ideals, engaged research, etc.). We also build on notions of heterogeneous information networks (Shi, Li, Zhang, Sun, & Yu, 2017), which are essentially conformed by "multiple types of objects as well as multiple types of links, indicating different sorts of interactions among these objects" (Sun & Han, 2013).

In line with the above, it has been suggested that social media tools (also known as Web 2.0 tools) "come with a number of other important functionalities that enable novel forms of social interaction" (Katrin Weller & Peters, 2012). Thus, the study of such interactions between social media users, their online activities, and scholarly objects conforms to a new area of science studies, dubbed the *Social-Media Studies of Science* (Costas, 2017; Wouters, Zahedi, & Costas, 2019). This more interactive perspective argues in favor of a shift from frequency-based metrics, the mere counting of social media mentions of scholarly outputs (i.e., the usual realm of altmetric research), to a stronger focus on the characterization, understanding, and modeling of interactions and relationships between the different *worlds* implicated in the mediation of science (science communication professionals, social media, journalism, citizen science, non-expert actors, activism as well as scientists), thus opening possibilities for the development of a relational approach in social media analysis defined as the study of *science-society interfaces*. From this point of view, attention is no longer limited to measuring the number of tweets or Facebook mentions a publication has received, and shifts to analyzing the *what*, *how*, *when*, and *who* (Haustein, 2018) of social media interactions between scientific and societal actors, or more minimally defined as *science-non science interactions*.[1] Previous theoretical, empirical, and technological developments have also paved the way toward these more interactive perspectives. For example, the framework introduced by Haustein et al. (2016) already suggested that one central aspect of the differentiation between diverse science metrics (including, but not restricted only to altmetrics) was the *type of engagement* between the user and the science object that a given metric is capturing (identifying three main categories of engagement: *access*, *appraisal*, and *application*). We argue that these categories may be extended to de-center the role of science in social media-based science communication, for example, in order to evaluate the role of scientific data objects as evidence base in wider public debates, where scientific research may be invoked to *mobilize*, *advocate*, and/or *criticize*. As Haustein et al. (2016) suggested, the different forms of engagement with science and their boundaries are actually *fuzzy*, fluid, to the extent that even the same social media acts may capture different forms of engagement. More recently, (Wouters et al., 2019) argued that social media metrics could be divided in those with a stronger *social media focus* (e.g., tweets, Facebook mentions, etc.) and those with a stronger *scholarly focus* (including here traditional bibliometric indicators, but arguably also metrics coming from platforms such as Mendeley, F1000, or ResearchGate and Academia.edu). The main rationale for this differentiation is grounded in Haustein et al. (2016) idea that acts falling in each of these two categories are associated with "norms substantially different". Thus, the communicative practices, modes of engagement, and contextual justification that social media users display in taking up a scientific output are likely to be different from those that would drive researchers to cite a paper or to appraise it in a peer evaluation process. Empirical research has found further indications of this difference between media-based and science-centric interactions with science objects, with multiple studies showing the weak correlation existing between most social media metrics and other science indicators such as citations, bibliographic characteristics, document types, etc. (Costas, Zahedi, & Wouters, 2015; Haustein, Costas, & Larivière, 2015).

New technological and methodological developments in altmetrics are also opening new perspectives on how social media metrics can inform broader debates about changing forms of engagement between science and society in a computational age. Recent work on the identification of individual scholars on Twitter (Costas, 2017; Costas et al., 2020; Ke, Ahn, & Sugimoto, 2017), as well as the identification of the social media presence of journals (Fraumann, Costas, Mugnaini, Packer, & Zahedi, 2016) or academic institutions (Adams, Gurney, & Marshall, 2007; Shields, 2016; Yolcu, 2013), point to the shift from an initial unidirectional perspective in altmetrics (focused on quantifying the reception of science objects on social media) toward a more bi-directional, relational perspective, in which a variety of forms of engagement with scholarly entities by a variety of actors on social media platforms can be studied. For the operationalization of more relational and bi-directional perspectives on science-society engagement, network-based methodologies are well suited, as such perspectives can surface how diverse science-social actors and entities are brought into relation (coupled) in a social media environment. However, while social media analyses conducted within a communication science, media studies and Science and Technology Studies framework have already advanced *co-occurrence analysis* as a suitable social media research method (Borra & Rieder, 2014; Bruns & Burgess, 2015; Marres, 2017) the literature on social media analysis of scholarly communication lacks a proper discussion of the methodological possibilities of network analysis and the frameworks that could support its development. This is in contrast to scientometrics, where the analysis of networks couplings represents a well-established methodological tradition (e.g., collaboration networks, citation networks, semantic networks, etc.). As a response to this critical gap, the main aim of this paper is to provide a first conceptual systematization and generalization of the potential couplings and network constructions that become analyzable with altmetric data.

2 | HETEROGENEOUS COUPLINGS

Scientometric research focuses to a large extent on the analysis of two basic couplings among scientific documents, which are both based on citation relations: *bibliographic coupling* and *co-citation* (Boyack & Klavans, 2010). Bibliographic coupling happens when two documents cite the same document(s). Documents that cite the same documents are considered to be conceptually connected. Co-citation happens when two documents are cited by the same documents, also pointing to a conceptual connection between the co-cited documents. In addition, in the scientometric sub-area of webometrics, which conceptually has stronger links with altmetrics and social media links (Haustein et al., 2016), the terms *co-linking* (essentially equivalent to bibliographic coupling) and *co-linked* (equivalent to co-citation) were proposed by (Björneborn & Ingwersen, 2004), see also (Rogers, 2013). Figure 1 schematizes these two approaches of bibliographic coupling (co-linking) and co-citation (co-linked).

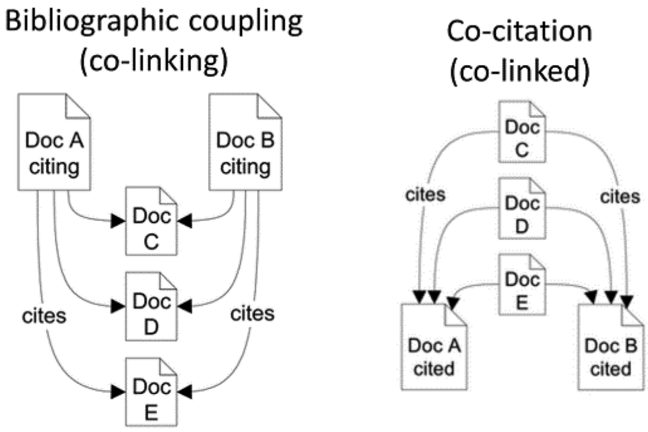

FIGURE 1 Bibliographic coupling (co-linking) and co-citation (co-cited) (source: Wikipedia). https://en.wikipedia.org/wiki/Bibliographic_coupling, https://en.wikipedia.org/wiki/Co-citation

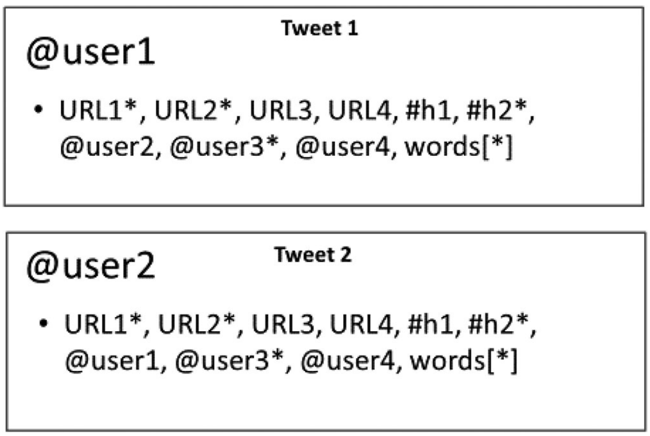

FIGURE 2 Constitutive elements of tweets for heterogeneous couplings. Elements followed by an * indicate that the element refers to any kind of science object (e.g., papers, datasets, researchers, universities, scientific journals, research topics, etc.). Elements without * refer to any kind of non-science objects

In social media analysis, similar methods have also been applied to analyze the co-occurrence of digital media objects and actors, in the form of bipartite hashtag-user networks, URL-user networks, and so on (Marres & Moats, 2015; Rieder, 2013). Social media research to date, however, has mostly analyzed non-directional co-occurrence networks and tends to treat these relations as a relative index of relevance and popularity. Considering the more diverse and *heterogeneous* nature of social media sources, acts, users, and their derived metrics (Haustein, 2016), particularly as compared to those recorded in science citation databases, the analysis of their relationships can bring into view also *more heterogeneous* forms of couplings between scientific and non-scientific objects and actors (Marres, 2017).[2] Thus, social media platforms like Twitter or Facebook do not only make available a more diverse range of media acts than citation analysis—for example, tweeting, retweeting, following, replying, linking, commenting, mentioning, liking, etc.; but also, unlike scientific journals, these platforms constitute a sort of meta-platform where (among others) news media, science communication, policy reporting, industry promotion, and civil society advocacy, intersect. Thus, from our perspective social media are heterogeneous thrice: in the *sources* (e.g., Twitter, Facebook, blogs, Mendeley, media URLs, DOIs, etc.), in the *actors* (e.g., researchers, citizens, journalists, organizations, etc.), and in their *interactions* (e.g., posts, retweets, tags, likes, shares, replies, comments, etc.). In this paper, we conceptualize heterogeneous couplings as the co-occurrence of science and non-science objects, actors, and interactions in online media environments.

2.1 | Modeling heterogeneous couplings: The example of Twitter-based couplings

In order to provide an initial concrete illustration of these heterogeneous couplings, we will focus on Twitter. Twitter is the most substantive altmetric source (after Mendeley readership) in terms of activity recorded (Robinson-García, Torres-Salinas, Zahedi, & Costas, 2014; Zohreh Zahedi, Costas, & Wouters, 2014). It is also one of the altmetric sources with the clearest *social media profile* (in contrast to Mendeley that arguably has a stronger *scholarly focus*) (Wouters et al., 2019), thus representing a good site to explore and operationalize the concept of heterogeneous couplings proposed here. We will discuss the possibilities of extrapolating the framework we propose for Twitter to other online media environments later on in the paper.

To begin with, we do well to describe the *constitutive elements* of a Twitter post (tweet) in order to define the possible couplings that can be derived from them (Figure 2).

Figure 2 schematizes the constitutive elements of two different tweets (tweet 1 and tweet 2). As it is shown in the scheme, each tweet[3] is produced by a different Twitter user (@user1 and @user2, respectively). Each tweet also contains a series of (optional) elements that we organize as follows:

1. *Links to external objects*, here marked as URLs. Conceptually, we distinguish *science objects* (marked with an *, as in URL1* and URL2*) and *non-science objects* (marked without an *, as in URL3 and URL4). For delineating science object, as in Haustein et al. (2016)

we adopt a broad perspective considering as science objects not only scientific documents but also individual scholars, research groups, departments, universities, journals, publisher, funders, and essentially any "entities acting within the scholarly community" (Haustein et al., 2016). As such, we argue that science objects can also include research topics, conferences, etc. and any substantive actors or objects related with the generation of new scientific knowledge.[4] Thus, URL1 and URL2 could be both links to papers, universities websites, or even individual researchers websites. In the case of non-science objects, these are links to external objects such as news articles, policy reports, campaign sites, industry and NGOs' websites, campaigns, blogs, social media posts, etc.

2. *Links to other Twitter users* through the use of mentions of other tweeters[5] (using the sign '@' to mention any other user in the system). These links can be considered "explicit" when the tweeter is directly mentioning—and addressing—the other user in the tweet, but they can also be the result of another action such as a retweet (in which the author of the initial tweet would be mentioned by default) or a reply. As for the linking of external objects, it is also possible to make the distinction between links to *science-related users* marked with an *, would include individual researchers, universities, scientific journals, science associations, etc. and links to non-science-related users, not marked by an *, and would include any other type of *non-science related users* (e.g., citizens, journalists, companies, NGOs, citizens associations, political or governmental organizations, bots, etc.).
3. *Links to other Twitter-specific textual/relational features*. An important socio-technical feature in Twitter is hashtags.[6] Hashtags are words preceded by a hash (#) and are typically used to signpost the topic of individual tweets (Pöschko, 2011), allowing Twitter users to disseminate their messages to larger audiences beyond their own set of followers. As a constitutive element of heterogeneous couplings, they may also play the dual role of being science-related, marked with an * (examples of these could be hashtags related to scientific conferences, scientific events, scientific journals, scientific topics, etc.); and non-science related (not marked with an *), being these any hashtag used on Twitter without a scientific relationship. Other Twitter features would include the mentioning to other tweets, retweeting,[7] modified tweets (that can be seen as a variant of retweeting), replying, liking, commenting, conversational tweets, following other users, etc. (boyd, Golder, & Lotan, 2010; Holmberg & Thelwall, 2014).
4. *Other textual elements* (e.g., words, sentences, topics, names, etc.) that can be included in the text of the tweets. In Figure 2 these are identified as "words". Conceptually speaking they could also have a science/non-science nature (marked in Figure 2 with [*]).

An important characteristic of the constitutive elements above is their heterogeneity, ranging from "objective" or "substantive" references to scientific information to "subjective" or "social" forms of interaction and hybrid formats (both substantive and organizational) like hashtags. This suggests that the analytic possibilities of "heterogeneous couplings" are relatively open-ended but also rich. Based on the different constitutive elements defined above, it is now possible to conceptualize different forms of Twitter couplings. In Figure 3, an incomplete set of examples of specific couplings based on Twitter interactions with science objects (i.e., URL1 and URL2) are presented. These include couplings of tweets, tweeters, and hashtags. These examples are not meant to be exhaustive (i.e., describing all possible couplings based on Twitter interactions) but to illustrate the diversity of the types of heterogeneous couplings Twitter, following the bibliographic coupling/co-citation parallels that can be established on the basis of the constitutive elements depicted in Figure 2.

As portrayed in Figure 3, it is possible to establish different couplings based on Twitter following the structure of the bibliographic coupling and the co-citation models. These couplings can be used to surface links between scientific objects on Twitter, and insofar as they follow the format of scientific citation, may be expected to foreground science-centered interactions and content relations on Twitter. There is however an important difference between heterogeneous couplings and the bibliographic coupling and co-citation models: the latter are confined within a single enclosed system, which broadly adhere to the same genre conventions (i.e., scientific publications and citations); while couplings found on Twitter combine at least two different information systems and genres (i.e., social media—tweets; and the scientific system—science objects). The heterogeneity that arises from systems being coupled is part of what justifies the consideration of these couplings as *heterogeneous* (in contrast with the more homogeneous couplings in scientometrics and citation analysis). Another reason for this heterogeneous nature of the couplings is the methodological potential of these for analyzing couplings across the science/non-science distinction by these means. This realization is then also important because it highlights the science-social media nature of these couplings (see also Wouters et al., 2019).

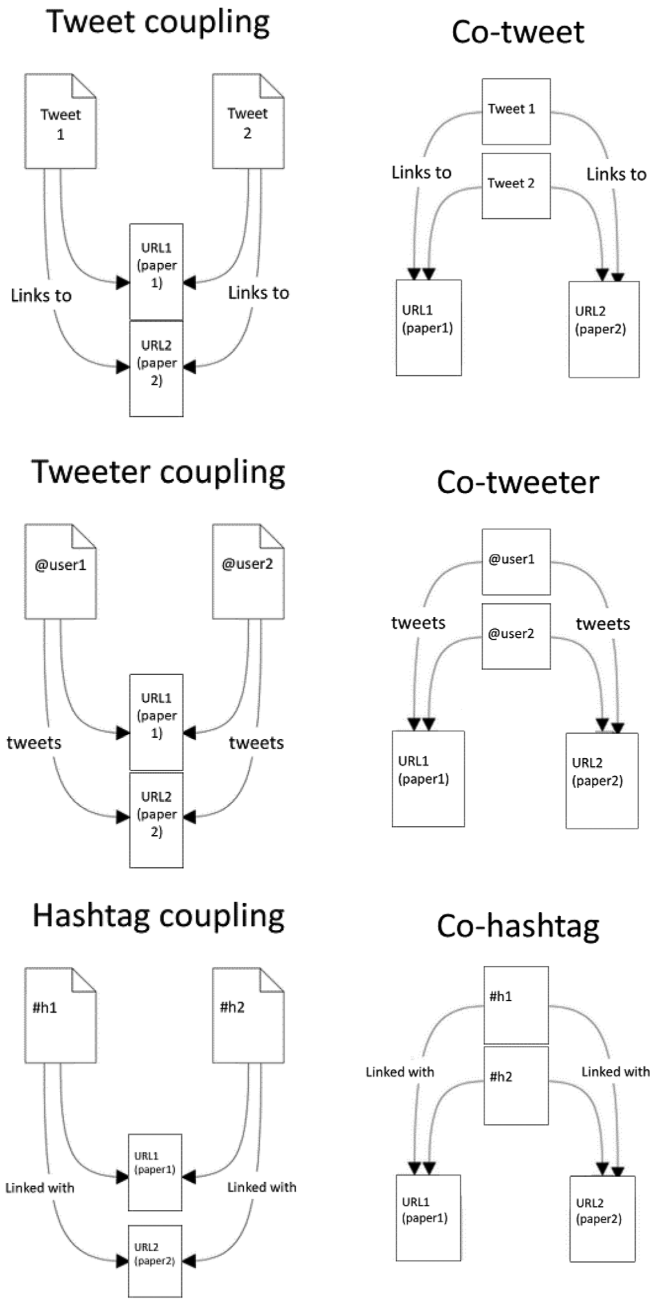

FIGURE 3 Heterogeneous couplings on Twitter based on bibliographic coupling and co-citation models

We talk about *tweet coupling* when tweets are coupled by linking to the same science objects (e.g., the same papers). In other words, the tweets are the *nodes* or *vertices* of the network, and the (count of) common papers are the *edges* or *links* (see Calero-Medina (2012) for an extensive discussion about networks in bibliometrics), resulting in a network of tweets coupled by their mentions to the same set of publications (or to any other set of science objects). We talk about *co-tweet* occurrences when science objects are coupled because they co-occur in the same tweets. In network terms, the science objects (e.g., the scientific publications) are the *nodes* of the network, and the (count of) common tweets become the *edges*, resulting in a network of science objects that are *co-tweeted*.[8]

Continuing the discussion of the examples in Figure 3, it could be argued that given the length restriction of 280 characters in Twitter (before it was 140), it cannot be expected that many tweets will link to many different science objects at a time. Therefore, heterogeneous couplings based on tweets may not always be very useful. A more robust option is the *tweeter*[9]-based (or account-based) models (graphs on the second row of Figure 3), where tweeters are coupled based on the number of common science objects they have tweeted (at a given point in time). As a result, and mimicking the tweet-based couplings, it is possible to talk about *tweeter coupling*, when tweeters are coupled because they *tweet* the same science objects. Thus, the *tweeters* become the nodes of the network, and the (count of) common science objects mentioned by them become the edges or the links among the tweeters. From a different perspective, we talk about *co-tweeter* networks when science objects *are mentioned* by the same tweeters; or simply put, the science objects are the nodes of the network and the (count of) common Twitter users mentioning them are the edges.

The third example presented in Figure 3 hints at the possibility in social media of establishing couplings based on specific social media *socio-technical features*, in this case, hashtags. Thus, we talk about *hashtag coupling* when hashtags are the nodes of the network, while the (count of) common science objects (e.g., publications) with which they co-occur are the edges. Similarly, we can talk about a *co-hashtag* network when science objects are coupled based on the common hashtags they *co-occur with*. In other words, the science objects are the nodes of the network, while the (count of) common hashtags that have been mentioned together with the science object become the edges. These examples of couplings based on hashtags point toward a third type of coupling that can be established based on Twitter-specific *socio-technical features*.

From the descriptions of the examples above it is important to remark that the focal point of the analyses may be different depending on the perspective adopted. Thus, in some cases the focal point (i.e., the nodes) is on the non-science objects (e.g., the tweets, tweeters, or hashtags); while other times is on the science objects (e.g., scientific papers, journals, etc.). Other times is the science/non-science combination what matters (e.g., clusters of hashtags and author keywords that have been coupled on Twitter). Thus, different from the bibliographic coupling and co-citation approaches illustrated above, in which the same set of documents are analyzed from different perspectives depending on when they are nodes or edges, in the heterogeneous coupling models, the perspectives are more diverse and need to be chosen by the researcher. Below we provide some extrapolations of the heterogeneous coupling model in order to show how these more complex perspectives can easily be incorporated within the heterogeneous couplings discussion.

2.2 | Generalizing heterogeneous couplings

All previous examples demonstrate the possibility of establishing diverse types of co-occurrence couplings based on tweets' constitutive elements and their relationships with science objects. However, the same types of couplings can easily be detected in other online media environments, for example, blogs (posts), Facebook (mentions), Mendeley (readership), etc. In this section, we discuss the possibility of extrapolating similar types of couplings to other media environments and forms of online interaction.

We argue that the analysis of heterogeneous couplings enables us to examine the interaction between two types of objects in social media environments: science and non-science objects. As mentioned before, with science objects we refer to any substantive actors or objects related with the generation of new scientific knowledge. As non-science objects, also from a broad perspective, we refer to both actors and objects without a specific scientific nature. We acknowledge that the boundaries between a science and non-science objects are not always clear, therefore, a better denomination for non-science objects in this context would be *social media objects*, in which the non-science property of the object is conferred via its social media nature. In practical terms, social media objects would take the form of acts (e.g., tweets, mentions, shares, etc.), users (e.g., tweeters, bloggers, commentators, etc.), or specific socio-technical features (e.g., hashtags, likes, etc.) from social media platforms, interacting with science objects. To simplify this idea a bit further, we argue that heterogeneous couplings can be distinguished based on what is being *connected* (i.e., the nodes) and what is *connecting* (i.e., the edges) via social media interactions. Thus, when *science objects are connecting* and *non-science (or social media) objects are connected*, we could talk about social media coupling. At the same time, when *science objects are connected* and *non-science objects are connecting* we could talk about co-social media linking.

The generalization presented in Figure 4 is intended to be broad in terms of all possible interactions that can be established between social media (through their different acts, agents, and socio-technical features) with any possible science object (e.g., papers, researchers, scientific organizations, journals, scientific funders, or scientific topics).

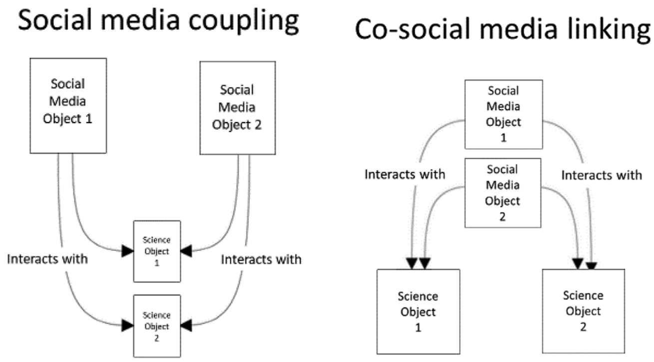

FIGURE 4 Generalization of heterogeneous couplings for social media objects and science objects

2.2.1 | Two-mode (bi-partite) network approaches of heterogeneous couplings

In the generalization presented above (Figure 4), it is still possible to see that there are two different perspectives: one focused on the coupling of social media objects (i.e., social media couplings) and the other one focused on the coupling of science objects via social media (i.e., co-social media linking). However, the ambition of this paper is also to demonstrate the bi-directional nature of heterogeneous couplings, in which both science and social media can be de-centralized as the main focal points of heterogeneous couplings. Thus, based on the generalization of heterogeneous couplings in Figure 4, it is also not difficult to derive the possibility of two-mode networks approaches (i.e., networks with two sets of nodes, and ties between the nodes belonging to the two different sets) that can unveil the optimum analytical potential of heterogeneous couplings. In these *two-mode heterogeneous couplings networks* science objects and social media objects are both *connected* and *connecting* elements in an indistinguishable manner. Probably the best way to exemplify this type of two-mode networks is considering a network of citations between blog posts and scientific papers. Both blog posts and scientific articles can cite indistinctively other blog posts and scientific papers[10] (see general example in Figure 5 left). Thus, blogposts and scientific papers can be simultaneously coupled since they cite (or are cited) by also blog posts and papers, in what becomes a two-mode network of both papers and blogs citations.[11] The possibilities of

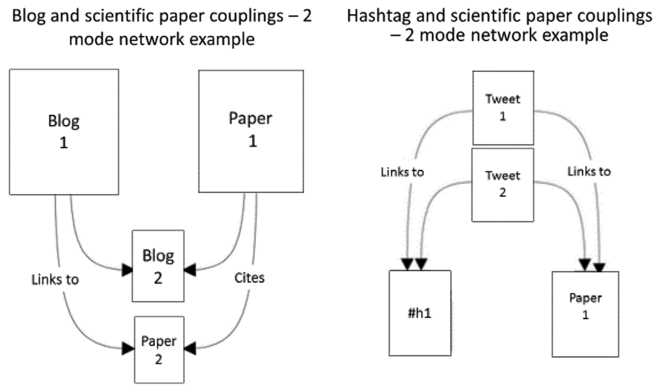

FIGURE 5 Examples of two-mode networks of blogs and scientific papers (left); and hashtags and scientific papers (right)

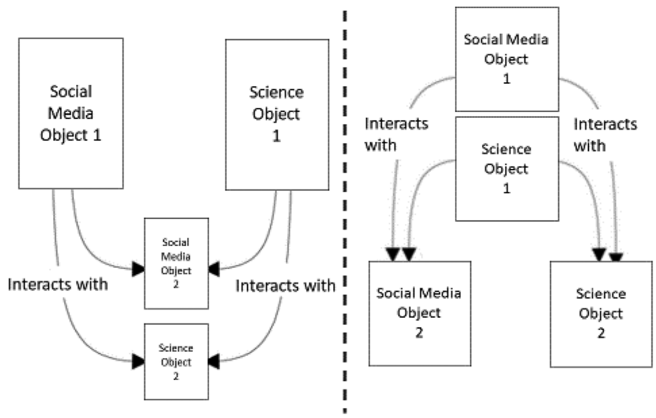

FIGURE 6 Generalization of *n*-mode networks based on heterogeneous couplings

these two-mode networks go beyond our example of blog posts, and conceptually speaking it could be extended to any social media object, thus including (re)tweets, Facebook wall posts, online comments, etc. that can both link to science objects or be linked by science objects (e.g., scientific publications citing tweets or any other social media object). In this line, perhaps an interesting example of a very common type of two-mode network, often used in altmetrics, is the combined count of original tweets and retweets (a count provided by many altmetric data provider such as Altmetric or PlumX). Following the notions by (Weller & Peters, 2012), retweets would be both linking to a science object (e.g., a paper—an "external citation" in Weller & Peters' notion) and to an original tweet (an "internal citation"). Usually, the distinction of retweets and original tweets is not discussed in the altmetric literature, although it has recently been discovered that the dependency of retweets on original tweets is of paramount importance in Twitter studies of science (Fang, Dudek, & Costas, 2020). Thus, if a tweeter deletes an original tweet linking to paper that has been heavily retweeted, all the retweets will also disappear, together with the original tweet, from the tweets count of the paper, which in occasions may have a substantial effect on the Twitter analysis of publications (Fang et al., 2020). This example highlights the fundamental distinction between original tweets and retweets, and clearly illustrates and reinforces the importance of being aware of the type of couplings that each altmetric indicator may be capturing.

Another interesting example of a two-mode network is the network of papers and hashtags tweeted together (Figure 5, right). Thus, papers and hashtags are coupled via their simultaneous presence in tweets, allowing for a two-mode network map that would plot both hashtags and papers connected by the number of tweets that have co-linked simultaneously both.

Based on the previous idea of two-mode networks of heterogeneous couplings, it is also possible to suggest a further enlargement of the multiplicity of social media objects that can be combined with science objects. For example, one could combine in the same analysis Twitter users, Twitter hashtags, and author keywords (see an example in [Hellsten & Leydesdorff, 2017]). Figure 6 schematically illustrates that multiple social media objects can simultaneously be combined with either other social media objects and/or science objects, in what essentially becomes *n*-mode network types. It is precisely this type of *n*-mode networks that illustrate how the heterogeneous couplings framework does not take a science-centric perspective, but an interactive one, in which science objects and social media objects (or non-science objects) can be combined in multiple ways. Thus, the possibilities of these *n*-mode networks could include the analysis of the Twitter activities (including tweets that do not link to scientific papers like in traditional altmetrics) of tweeters that are scholars, or the combined analysis of tweets, blogs, and papers that have been cited in scientific publications. Simply put, the framework of heterogeneous couplings can accommodate nearly any form of science/non-science recorded interaction, allowing them to simultaneously be combined in multiple ways.

3 | IMPLEMENTING HETEROGENEOUS COUPLINGS IN ALTMETRICS

During the past years, research in altmetrics has already produced (implicit or explicit) examples of heterogeneous couplings usage, although until now no systematic discussion of these couplings and networks has yet been provided, sometimes creating even situations of confusion. In this section, we illustrate the operationalization and analytical possibilities of heterogeneous couplings with some of these examples from the literature.

3.1 | Heterogeneous couplings based on social media couplings

In this section, we discuss the most important development regarding the studies in which different social media objects, typically Twitter users, were coupled based on their similar connection to science objects (usually scientific papers).

3.1.1 | Communities of attention and audiences

One of the first examples was the development of *communities of attention* proposed by (Haustein et al., 2015), which are based on the coupling of Twitter users who related to the same set of publications. In that study, over 125 thousand Twitter users were studied and categorized based on their engagement with scientific publications. The study found that tweeters of scientific papers tend to describe themselves in their Twitter profiles with a combination of academic, personal, and topical terms (a similar pattern as also as in (Díaz-Faes, Bowman, & Costas, 2019). Another example of communities of attention is the analysis of (Van Van Schalkwyk, 2019) on the communities of tweeters involved in the anti-vaccine campaign, identifying groups of tweeters pro and anti-vaccine mentioning different sets of scientific publications. In a similar fashion, (Alperin, Gomez, & Haustein, 2018) studied the *audiences* in Twitter of a sample of open access publications. They also analyzed the follower relationships of these tweeters to conclude that most of their sampled publications were shared within single-connected communities. The study of audiences as in the (Alperin et al., 2018) case can be seen as a particular example of the analysis of users coupling, in which social media users (i.e., the audience) are connected because they have interacted with the same set of science objects. This type of analyses can be linked to the arguments of (boyd, 2010) in which publics and audiences can be seen as synonyms to refer to “a group bounded by a shared text, whether a worldview or a performance”, which in the case of communities of attention can be seen as communities sharing a scientific idea or ultimately a research outcome.

3.1.2 | Follower/followees couplings

The follower/followee socio-technical feature that is inherent to most social media platforms (e.g., Twitter, Facebook, etc.) also allows for heterogeneous couplings when at least one of the follower/e can be related to a science object (e.g., scholars on Twitter, social media accounts of universities, social media accounts of scientific journals, etc.). Thus, for example (Robinson-Garcia, van Leeuwen, & Rafols, 2018) identified the communities of followers of two researchers aiming at identifying potential interactions between academic and non-academic stakeholders as they could be measured by their composition of the followers network of researcher. A similar approach was applied by (Shields, 2016) studying the follower/followee relationships of the Twitter accounts of 221 universities extracted from different university rankings. These authors highlighted three important factors in the follower/followee network composition of universities: geographical, ranking-related, and mutual acquaintance. In this study, the heterogeneous couplings here are determined by the coupling of universities (which simultaneously are the science object and the social media agent) and are connected by the Twitter technical feature of *following* (or being *followed*) by other universities.

3.1.3 | Hashtag-based couplings

Twitter hashtags allow the identification of collections of tweets with the same hashtag, conforming to something that can be seen as the same *conversation* about a given topic. As explained above, hashtags also allow for forms of heterogeneous couplings. One of the first examples of showing the possibilities of couplings of hashtags was (van Honk & Costas, 2016), developing networks of scholarly related hashtags. A similar approach was also used by (Haunschild, Leydesdorff, Bornmann, Hellsten, & Marx, 2019) for the analysis and clustering of hashtags around climate change research. (Bautista-Puig & Dudek, 2019) proposed the use of hashtags related to Sustainable Development Goals (SDGs) as a form of identifying SDG-related research, considering that publications that are tagged with the same SDG hashtag are related to the same SDG, in what can be seen as a genuine use of a co-hashtag analysis to classify publications. Other studies also focused on the analysis of hashtags related to scientific communication (Letierce, Passant, Decker, & Breslin, 2010; Katrin Weller & Puschmann, 2011) applying approaches that can be related to the idea of heterogeneous couplings discussed here. Another variant form of hashtag coupling includes the analysis of hashtags around scientific conferences (Bombaci et al., 2016; Chapman, Mayol, & Brady, 2016; Gonzales, 2014; Wilkinson, Basto, Perovic, Lawrentschuk, & Murphy, 2015), or scholarly-relevant events or reports, like the Intergovernmental Panel on Climate Change (IPCC report—(Pearce, Holmberg, Hellsten, & Nerlich, 2014). Similarly, (Marres & Gerlitz, 2016) proposed the use of co-occurrence of hashtags as form of tracking "issue dynamics" in their broader framework of "interface methods".

3.2 | Heterogeneous couplings based on co-social media linking

3.2.1 | Co-tweeting analysis

Didegah and Thelwall (2018) provided an excellent application of heterogeneous couplings based on what at the time they explicitly termed as "co-saved" and "co-tweeted" networks. In their study they used a "user-centered" approach by studying the coupling of publications by the same tweeters (in different tweets) and by the same Mendeley users (in their individual libraries). Essentially, their *connecting elements* were social media agents (i.e., tweeters and Mendeley users), and the *connected objects* were Web of Science publications, in what can be seen as a one of the first examples of *co-social media linking* analysis. Applying the heterogeneous coupling framework proposed here, we would argue that regarding Twitter, in fact they performed a *co-tweeter* analysis (rather than a *co-tweet* analysis), since as per our model in Figure 3, they focused on the coupling of papers by tweeters (i.e., the agents) and not just in tweets (i.e., the acts). Another example in which certain level of confusion could be found is in the *tweet coupling* suggested by (Hassan et al., 2020), which they defined as the "similarity between two or more scientific documents if one or more Twitter users mention then in the tweet(s)". In our framework, the proposal by Hassan and colleagues would fit better in the co-tweeter analysis, and conceptually speaking is virtually the same approach as described by (Didegah & Thelwall, 2018). These examples clearly exemplify how our heterogeneous couplings framework approach would help to unify and simplify these type of analyses.

3.2.2 | Co-(Mendeley)readership analysis

Another source of relevant couplings (and network analytical possibilities) come from the online reference manager Mendeley (Haunschild, Bornmann, & Leydesdorff, 2015) in the form of Mendeley users' savings of publications (Zohreh Zahedi, 2018). One of the first proposals that could be related to the idea of heterogeneous couplings was suggested by (Kraker et al., 2015) on the explicit analysis of *co-readership*. According to these authors, co-readership happens "when at least one user has added the two documents to his or her user library" (Kraker et al., 2015). Thus, these authors analyzed clusters of papers based on the co-readership networks, in which the *connecting elements* are the Mendeley users (i.e., the social media agents) and the *connected objects* are the publications (i.e., the science objects). As mentioned above, a similar approach based on Mendeley co-savings was developed by (Didegah & Thelwall, 2018). From another perspective (Haunschild, & Bornmann, 2015a) developed networks of Mendeley socio-technical features, namely the subject categories of Mendeley users and their countries. In practical terms, the connected elements are the Mendeley users' countries and fields, while the connecting element is the publications in which the features co-occur. Thus, based on our framework, it could be argued that these rather correspond to forms of *readers' features coupling networks*, rather than a co-readership analysis.

3.3 | N-mode networks based on heterogeneous couplings

Two publications that use the *n*-mode type of heterogeneous couplings are (Haunschild et al., 2019) and (Hellsten & Leydesdorff, 2017). In the first case (Haunschild et al., 2019), the authors study the relationship between author keywords in climate change-related publications with the hashtags used in the tweets of the same set of publications. Although the authors never simultaneously combined author keywords and hashtags in their analysis, implicitly they were studying the relationship between hashtags and author keywords in what conceptually would be a two-mode type of network of hashtags (the Twitter feature) and author keywords (the science object). Probably a more implicit implementation of this idea was applied in (Lyu & Costas, 2019), where author keywords of publications related to the topic of "Big data" were combined with the hashtags from the tweets mentioning the same set of publications. This approach allowed the authors to study the similarities between the author keywords and the hashtags by the Twitter audiences.

Finally, the (Hellsten & Leydesdorff, 2017) paper, explicitly mentions the two-mode network type in the combination of both hashtags and Twitter usernames from tweets. These authors also go further to suggest a three-mode network in which hashtags, Twitter users mentions, and authors are all combined. They proposed the idea of *n*-mode networks in what they call the "whole matrix approach". They proposed that in these *n*-mode networks, all sorts of actors and topics are simultaneously combined, in a very similar fashion as we proposed in our heterogeneous couplings proposal. A conceptual difference between the heterogeneous couplings and the "whole matrix approach" is that the latter follows an actor-network terminology and focuses on the combination of social actors and topics, while the first relates to all forms of science-non science interactions, combining both actors and objects. In many practical cases, however, the "whole matrix approach" would be equivalent to the heterogeneous coupling approach, and vice versa.

3.4 | Envisioning heterogeneous couplings in social media research

All the examples discussed above illustrate how the idea of the heterogeneous couplings approach has been already an important latent element in the development of social media research. However, the lack of a systematic discussion of the possibilities of these network approaches has already caused confusion and inaccuracies in the way these networks were framed and discussed. The availability of such a framework could have supported the conceptual and empirical discussions of most of the previous research approaches described in section 3. Thus, for example the work by Haunschild and Bornmann (2015a, 2015b) could have been supported to clarify the "readership coupling" nature of their own work. Similarly, the work by Hassan et al. (2020) and Didegah and Thelwall (2018) would have counted with a common framework to frame their work as *co-tweeter* analyses, instead of considering their study as a *tweet coupling* analysis (in the case of Hassan and colleagues) or a *co-tweet* analysis (in the case of (Didegah & Thelwall, 2018)). Moreover, the heterogeneous coupling framework has value for the more traditional types of altmetric studies. For example, the typical basic counts of tweets or tweeters of scientific publications, which are currently provided by most altmetric data providers like PlumX or Altmetric.com (Zahedi & Costas, 2018), could now be framed as aggregations of tweet and tweeter coupling analyses, in which the tweets or the tweeters (i.e., the *nodes*) coupled around a publication (or a set of publications) would be aggregated and counted.

Overall, we believe that our proposal provides a common conceptual framework and a relatively basic terminology not only for already established altmetric indicators, but also for future analysis of all sorts of network perspectives of science-non science interactions captured via social media and altmetrics. While our approach is still under development, we believe that based on the current proposal of heterogeneous couplings it is already possible to envisage new applications of social media metrics in social media research. Some of these applications do not need to have been implemented yet, but based on our conceptual framework they are, at least, theoretically possible, since it makes space for heterogeneity in the analysis of science-society interaction. For example, based on the idea of communities of attention, it is possible to envision new analytics (and metrics) related to the typologies, diversity, growth, etc. of science-society *audiences*. This type of audience (or *networked publics*) studies, could be related not only to how different actors—scientific, professional, policy, advocates, everyday actors—interact among themselves, but also to how they interact with information (as discussed by (boyd, 2010; Burgess, Galloway, & Sauter, 2015; Langlois et al., 2009). More practically, we argue that knowledge organizations, such as universities, may become interested in knowing whether publics beyond scholarly communities interact with science, in a similar fashion as discussed in Alperin et al. (2019). Similarly, science journalists may be interested in the *cognitive and semantic (dis)connectedness* among different publics, for example, by studying the cognitive or semantic differences between different audiences, thus being able to identify potentially interested audiences in a specific research topic.

Using approaches based on the ideas of "co-hashtag" and "hashtag couplings" it would be feasible to develop *recommendation systems* and more interactive and dynamic *dissemination strategies of science*. For example, research libraries could develop recommendation systems in which users would receive news of relevant publications based on relevant co-hashtag filters. Other examples of recommendations systems approaches could be based on the co-occurrence of researchers activities on social media (e.g., (Hadgu, 2015; Younus, Qureshi, & Manchanda, 2014). The idea of hashtag coupling can also be seen as a new form of *social tagging of science*, in line with Peters (2009). Moreover, forms of social co-hashtag analytics could be applied for advanced *field delineation* systems (with relevance for scientometric research), particularly when research fields are new, have a low coverage in bibliographic databases, or have imprecise boundaries (e.g., as in the case of delineating SDG-related research proposed by (Bautista-Puig & Dudek, 2019)).

Finally, the more complex forms of heterogeneous couplings, mostly characterized by two-mode or *n*-mode types of networks have also direct practical applications. For example, the *evaluation of scholarly communication strategies* by determining the (mis)alignment between science concepts and their social media interpretations, could have relevance for science communication offices, in order to evaluate their effectiveness in science communication. Moreover, the ability of studying the disparities between science-objects (e.g., author keywords) and social media objects (e.g., by Twitter hashtags) can open the door to identifying potential misuses of scientific information on social media. For example, it would be possible to identify communities of attention strongly connected via retracted publications, or detect Twitter debates in which the hashtags employed are contrary to the intended content of the publications.

3.5 | Toward the modeling of science-non-science interactions

Although we start from a relatively modest perspective (i.e., the modeling of science-social media interactions), the ambition behind the framework of heterogeneous couplings is to cover more forms of science-non science interactions, including for instance interactions that leave traces in non-digital forms (e.g., an event, a report, etc.). The framework of heterogeneous couplings also opens the door for more strategic foresight studies of emerging matters of scientific and societal concern. These studies (Burgess et al., 2015; Pearce, Niederer, Özkula, & Sánchez Querubín, 2019) draw inspiration from a concept developed by actor-network theorist Michel Callon and colleagues from the 1980s onwards (Callon, Lascoumes, & Barthe, 2009; Callon & Rip, 1992) to conceptualize a relational space where symmetrical encounters between representatives of science and the public can take place. This is understood as encounters where neither science nor the public dictates the terms of the debate unilaterally; the terms emerge from the exchanges between them. Is this model transferable to social media environments? While it is clear that social media like Twitter facilitate interaction among heterogeneous entities, a relational approach is facing at least two crucial challenges today: on the one hand, contemporary social media communication strategies are re-asserting asymmetrical approaches to science-society communications, with impact-driven, influencer-based publicity models in the ascendancy. On the other hand, symmetrical approaches to science-society interaction face challenges from fake news, misinformation, and disinformation campaigns, which require new strategies for discerning and differentiating among science's publics. The analysis of heterogeneous coupling may be deployed in relation to both these challenges, as the detection of heterogeneous interactions can surface alternative science communication ecologies. We believe that the key strength of the heterogeneous couplings framework, in this regard, is that it provides an adaptable framework, in which many different kinds of science-non science interactions could be included and studied, in varying social media environments. In this regard, our approach to the analysis of heterogeneous couplings can contribute to wider efforts in digital media studies and STS to analyze *hybrid forums* on social media platforms.

4 | CONCLUSION

In the seminal *Altmetrics Manifesto* (Priem, Taraborelli, Groth, & Neylon, 2010), altmetrics were conceptualized as both science filters and alternative forms of capturing impact outside the academia. Interestingly, these early propositions could be seen as instances of heterogeneous couplings, in which non-scientific elements (e.g., the number of tweets to papers) would serve as filters of science objects (e.g., by identifying the most tweeted publications), denoting reception, and interest beyond the academia itself. This reinforces the importance of the conceptualization of these science-non science interactions, in order to be able to contextualize and further unveil the full potential of altmetrics. We argue that a better understanding of the couplings and interactions between social media and science has the potential to pave the way toward more advanced, relational, and multi-dimensional science-society studies. In this paper, we provide a first step in order to fill this gap. We do so by introducing such conceptualization in the form of a framework of science and social media interactions in what we call *heterogeneous couplings*. This framework is adaptive enough to encompass many different types of interactions (and social media platforms), thus reducing the "dependency" on existing altmetric sources—seeing as a *grand challenge* in altmetrics (Haustein, 2016)—being useful for other present and future forms of science/non-science interactions and social media platforms. We conclude that the framework of heterogeneous couplings has specific relevance for advancing research agendas in altmetrics, insofar as it can inform a relational approach to analyzing science-society relations with and through social media. However, the conceptualization of heterogeneous couplings has potential relevance not only for the field of altmetrics, but also for the study of science-interactions. Thus, the heterogeneous couplings framework can be applied to other types of media, such as newspapers (in paper), magazines, television shows, documentaries, movies, radio broadcasts, and other forms of communication across science and society. As such, an important advantage of the heterogeneous couplings model is that it has a strong relevance not only for altmetric research, but also for broader range of social (media) studies of science (Costas, 2017), science and technology studies (STS), science of science, science communication, public understanding of science, research evaluation, scientometrics, and other research fields with an interest in studying science-society interactions.

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ORCID

Rodrigo Costas https://orcid.org/0000-0002-7465-6462
Sarah de Rijcke https://orcid.org/0000-0003-4652-0362
Noortje Marres https://orcid.org/0000-0002-8237-6946

ENDNOTES

[1] We include this more minimal distinction here in order to flag that "Science" and "Society" is not already constituted as categories in social media, and should thus not be taken for granted in their analysis. How to adequately operationalize these categories is a methodological question this paper takes on. Society is comparatively speaking more difficult to operationalize than science, which is more easily identifiable in institutional terms, and for this reason, we expect it will sometimes be necessary to rely on the more minimal distinction between science-non-science. The latter was proposed to us by Maria Puig de la Bellacasa. Personal communication, May 2019.

[2] See also (Marres, 2017, pp. 102–103) for a discussion on how online media confront the sociology of science with heterogeneous networks, and pp. 108–110 for a discussion of co-occurrence as an empirical measure deployed in 1980s sociology of science and 2000s analysis of co-occurrence networks on the Web (in link analysis) and in social media (hashtags analysis).

[3] The same model could be applied also to retweets. A tweet and a retweet can be considered Twitter acts of a different nature (Haustein et al., 2016) and according to (Weller & Peters, 2012) they can be seen as two different forms of Twitter citations, being retweets a form of internal (or Inter-Twitter) citation, in which a retweet would "cite" an original tweet. For now we do not delve into the distinction between these two in order not to complicate our discussion further, although later on when we talk about *n*-mode type of networks, we will provide an example on how the distinction between original tweets and retweets can also play a role in the configuration of heterogeneous couplings.

[4] It is important to make this analytical distinction, even though it is difficult to identify scholarly actors in a systemized manner, since Twitter does not provide any categorization of actors mentioned in the tweets. This contrasts with the identification of research products, since they have specific identifiers (e.g., DOIs, PMIDs, etc.) making more feasible their identification by altmetric data aggregators; this also explaining why the vast majority of altmetric research has focused on the study of research products and not actors.

[5] We distinguish between Twitter users and tweeters. The latter includes registered users who send tweets. The former presents a broader category, which also includes users who are registered but do not tweet and those who are not registered but consult Twitter. This broader category has special relevance for us, as our interest is in social media as a space for broadening science-society engagements beyond a narrow set of already active, established users. However, the engagement of users is more difficult to measure than that of tweeters.

[6] Twitter hashtags were introduced by users and subsequently promoted by Twitter itself as a way to navigate content (Halavis, 2014) and they have been considered an important socio-technical feature that surfaces thematic connections for users and analysts alike (Holmberg, Bowman, Haustein, & Peters, 2014).

[7] It could be argued that a re-tweet is just a link to another tweet.

[8] This is a term also used by (Didegah & Thelwall, 2018), which in our model is a simplified way of referring to *co-tweet*.

[9] Understood here as a Twitter user that engages in tweeting. In the following, we will use *tweeter* to strictly refer to registered Twitter users engaging in heterogeneous couplings, leaving *Twitter user* for the combination of both active (tweeters) and passive users.

[10] In altmetric research, citations from blogposts to papers have been extensively studied (Shema, Bar-Ilan, & Thelwall, 2012, 2014, 2015). It is also possible that scientific articles cite blogs among their cited references. Therefore, both blogs and scientific articles can cite each other establishing bi-directional blogposts-papers linkages.

[11] Another example of this kind of *bi-directional* 2-networks could be the network of Wikipedia entries and scientific papers, in which both Wikipedia entries and scientific papers cite each other indistinctively (i.e., papers cite Wikipedia entries and other papers, and Wikipedia entries cite scientific papers and other Wikipedia entries).

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