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Who, what, why? An exploration of JoVE scientific video publications in tweets

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Abstract
This paper investigates how and why scientific video articles are communicated on Twitter. We use video articles published in the Journal of Visualized Experiments (JoVE) as our objects of study. We harvested tweets from October 2011 to November 2015 that contained one or more JoVE links. These tweets "citing" JoVE articles were analyzed both statistically and qualitatively. In this paper, we present the distribution of these tweets, with a closer look at the affordance use of Twitter including hashtags and mentions. In addition, we conducted a content analysis of the sampled Twitter accounts and tweets. We present the coding schemes and results of both Twitter user accounts and tweets text. In addition to the analysis of the coding results, we discuss the content of the tweets with particular attention to issues including the video/visual feature mentioned, the role of Twitter bots, and self-promotion of different stakeholders in the Twitter communication of JoVE video publications.

Keywords Altmetrics · Scholarly communication · Twitter · JoVE · Participation in science

Introduction

Scientific research and education are increasingly relying on a more diverse array of content types. Historically, scientific articles have included text, and accompanying figures, graphs, and images. Today, digital articles may include more multimedia types,

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including videos. Unlike text, the videos offer unique benefits by leveraging our visual perception in comprehending ideas and feelings (Pasquali 2007). Pasquali (2007) argues that because a video includes “information such as color, position, duration, shape and motion,” it is the “optimal format for transmitting the manifold details of new protocols or technical procedures.”

Academic uses of videos both in education practices (Jones and Cuthrell 2011) and for research purposes (Kousha et al. 2012) have been studied. Prior work on the usage of videos for educational purposes in the arts and humanities (Brook 2011; Cayar 2011; Hoskins 2009; Muniandy and Veloo 2011; Rees 2008) and in science and medicine education (Clifton and Mann 2011; Fernandez et al. 2011; Franz 2012; Kaw and Garapati 2011; Knösel et al. 2011; Settle et al. 2011) has suggested that videos can help enhance students’ learning outcomes. Adding to the educational value of traditional textbooks and textual scientific articles to researchers, videos can help facilitate the learning process of the essential knowledge and skills to their research, thus improving the efficiency and accuracy of their work. Using videos to communicate scientific protocols instead of using textual descriptions is particularly important in experiment-oriented disciplines. Therefore, we are interested in understanding the means by which scientific videos are disseminated and discussed in scholarly communities, specifically, online communities on Twitter.

The microblogging service Twitter is one of the most important altmetrics data sources. Scholars discuss research-related topics and communicate with others in the field on Twitter (Van Noorden 2014). According to Haustein et al. (2015), about one-fifth of current journal papers receive at least one tweet. Academic activities on Twitter have been extensively studied by altmetrics researchers. Priem and Costello (2010) explored how and why scholars “cite” articles on Twitter. Holmberg and Thelwall (2014) investigated the disciplinary differences of scholarly communication on Twitter. Holmberg et al. (2014) studied astrophysicists’ activities on Twitter with a particular focus on their tweet construction and affordance use. Eriksson-Backa et al. (2016) explored the semantic content of tweets communicating on the topics of diabetes and diets. Tsou et al. (2015) investigated the identity of the tweeters who had tweeted at least one link to an article in one of four leading journals. Vainio and Holmberg (2017) examined the Twitter profile descriptions of researchers in science. Haustein et al. (2016) examined the role of automated accounts (Twitter bots) in tweets to arXiv articles. Studies have also examined Twitter altmetrics with citations and other altmetrics (e.g., Thelwall et al. 2013). In general, large-scale quantitative studies paint a broad picture of the landscape of Twitter scholarly communication but may be somewhat limited by the lack of the qualitative aspects of the data.

Existing research has been mostly focused on YouTube videos as scholarly information sources. Here we investigate a peer-reviewed scientific journal publishing curated videos, the Journal of Visualized Experiments (JoVE). JoVE is a 10-year old journal with nearly 7000 publications to date. Professional videographers and editors assist in producing videos to visualize methods, data analysis, and results. According to JoVE’s website (JoVE 2017), JoVE is devoted to helping researchers understand complicated experimental techniques and methods, both to make them easier and quicker to comprehend, and to aid in reproducibility. Many of these peer-reviewed video articles are observational and experimental protocol videos in the physical and life sciences. In this study, we analyze tweets that have at least one link containing the DOI of JoVE video articles. The communication of video articles has not been the focal point of previous social media impact research. By focusing on this specific subset of research documents, we aim to contribute to a better understanding of how and why scientific videos are tweeted.

To better understand the impact tweet counts capture, it is important to identify user types and their level of engagement (Haustein and Costas 2015). Therefore, this exploratory study is driven by the following research questions:

1. Who tweets JoVE articles? (account identity, gender, and Twitter bots' role)
2. How do they tweet JoVE articles? (including elements included in the construction of tweets, sentiment, and affordance use such as hashtags and mentions)
3. Why do they tweet JoVE articles? (motivation of tweeting)
4. Are video/visual elements specifically emphasized in the tweets of JoVE articles?

Methods and data

Altmetric.com provided the full dataset from October 2011 to November 2015 for this research. This dataset contains over 4.4 million records in JSON format. Each record represents one scholarly artifact (e.g., a journal article) and encompasses various types of altmetrics data about this artifact. Specifically, these altmetrics include those based on Twitter, Facebook, Blog, Wikipedia, News, Google Plus, Policy, Reddit, F1000, Weibo, Peer Reviews, Video, and Q&A. After learning the structure of this dataset, we established a relational database. In addition, we used a Python script to process the data and were able to successfully extract all the data of tweets that contain links to JoVE publications.

Overall, 7500 tweets were extracted, with data about their usernames and URLs, as well as the titles and URLs of the JoVE publications that they contain. To better understand the content of the tweets, we used another Python script to retrieve the tweets' text from Twitter using the Twitter handle. Because the altmetrics data were gathered earlier than we started to run the Python script (in September 2016), some tweets were shown to had been deleted. As a result, we further cleaned the data, and excluded 308 "HTTP Error 404: Not Found" ones and 798 "Twitter/Account Suspended" ones. In the end, for the exploration of tweets content related questions, our data consisted of only 6394 tweets. These data were processed one step further to extract the hashtags and mentions in the tweets text.

The frequently used hashtags and mentions were manually examined. The top 100 out of 928 hashtags were analyzed to better understand the purpose of using them. The top 50 out of 483 mentions were analyzed to confirm their account identity. Two coders participated in this analysis who were able to reach a complete agreement after two rounds of coding.

In order to gain a deeper understanding of the content included in the tweets and the motivation behind them, an additional content analysis was conducted by three authors. Considering that one Twitter user can post multiple tweets, we divided the coding of Twitter user accounts and Tweets into a two-step process. Firstly, we coded the Twitter accounts. We used a stratified sampling strategy to determine our sample. On the one hand, we only sampled users who had tweeted more than one tweet. On the other hand, considering that our purpose was to understand the tweeting behavior of people instead of bots, in this sample we eliminated three accounts which tweeted more than 20 JoVE articles and were confirmed by us to be bot accounts. Aiming to sample around 5% of the users, we sampled 104 Twitter accounts and 357 tweets. Both the account coding and the tweet coding processes consisted of multiple steps. When coding the tweets, three coders studied relevant literature and performed a trial coding with 30 tweets separately. The initial coding scheme was formed after our discussion about this first coding attempt. In the next step, 60 additional tweets were coded based on our initial coding scheme. Three coders discussed again, with a particular focus on the disagreement in coding and potential new categories. The final coding scheme of tweets was formed after that. In the following step, two coders coded 267 more tweets, reaching an average inter-rater agreement rate of 82%. The third coder reviewed the disagreement. When coding the Twitter accounts, a similar process was performed. The inter-rater agreement rate between the two coders was 91%.

Results

To present the results of our analysis, first, we provide the distribution of the tweets by users. Then, we analyze the frequently used hashtags to identify themes in the implicit purpose of using a particular hashtag. After that, we describe our findings about both the frequently mentioned users in JoVE article tweets, and the users who tweet JoVE articles. Finally, intending to provide a fuller picture of why JoVE articles are tweeted, we provide our coding of the motivation, elements of scientific articles mentioned, and sentiment of the JoVE article tweets.

Distribution of tweets

In total, 2153 Twitter users have posted 7500 tweets that contain JoVE article links. Figure 1 shows the skewed power-law distribution of tweets created by users. Specifically, the top 9 most active users (0.42%) have tweeted more than half of the tweets. By contrast, 167.6 users (77.84%) have only tweeted one JoVE article each. Almost 90% (89.13%) of users have either tweeted one or two JoVE articles.

More details of the top 10 most active Twitter accounts are shown in Table 1. According to our coding and discussion, the top 10 most active Twitter accounts include at

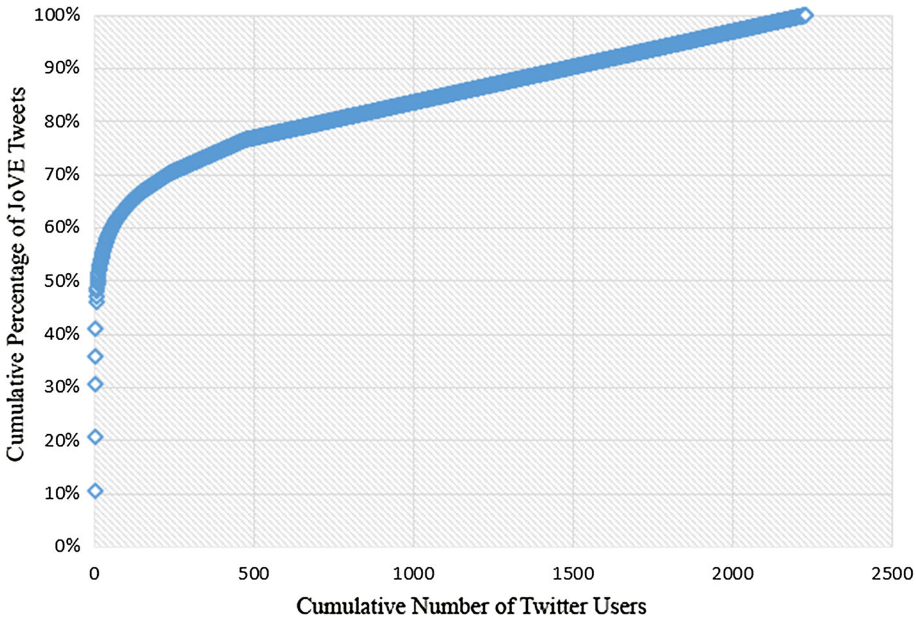

Fig. 1 Distribution of tweets created by Twitter users

Table 1 Top 10 most active Twitter accounts in tweeting JoVE articles

Account name	No.	%	Cumulative %	Coded account identity
JoVEJournal	1506	20.08	20.08	JoVE the journal
postechlibrary	800	10.67	30.75	Digital library
SfakianakisAl	394	5.25	36.00	Medical institution (bot)
Sfakianakismed	384	5.12	41.12	Medical institution (bot)
alsfakiahotmail	375	5.00	46.12	Medical institution (bot)
rnomics	121	1.61	47.73	Researcher of RNA related field (bot)
fly_papers	68	0.91	48.64	Paper feed
MPritsker	58	0.77	49.41	CEO, co-founder of JoVE
Medgadget	49	0.65	50.07	Medical technology news feed
semantic_bot	46	0.61	50.68	Paper feed (bot)

least five bot accounts. We used three criteria to determine if the accounts are automated bot users: (1) they identify themselves as bots; (2) they tweet paper titles without discussing their content (Thelwall et al. 2013); (3) they post a large number of tweets in a relatively short time period. We mark an account as a bot account if it meets the first criterion or the second and third criteria at the same time. The bots could be impersonated in institution accounts or individual accounts. The rest five accounts are also likely to be combining bot tweeting techniques with manual tweeting.

Frequently used hashtags

In total, there are 3235 hashtags (#) tweeted in all of these 6394 JoVE article tweets. In other words, approximately one hashtag is used in every two tweets. Among these hashtags, there are 928 unique ones, with the most frequently used one tweeted 862 times and the least frequently used one once. We present the top 10 in Table 2 below. With

Table 2 Top 10 most frequently used hashtags

Hashtag	No.	Coded purpose of use
#article	862	To indicate that this tweet is about an article
#Jove	188	To indicate that this tweet is about JoVE
#scivideo	139	To emphasize the visual/video feature of JoVE articles
#MySciVid	60	To emphasize the visual/video feature of JoVE articles
#Genetics	59	To specify relevant research areas/topics
#RNA	58	To specify relevant research areas/topics
#Cancer	56	To specify relevant research areas/topics
#neuroscience	56	To specify relevant research areas/topics
#Immunology	52	To specify relevant research areas/topics
#microbiology	40	To specify relevant research areas/topics

“#article”, “#Jove”, “#scivideo” (scientific video), and “#MySciVid” (my scientific video) being the top four, the rest six all specify relevant research areas or topics.

We further coded the top 100 frequently used hashtags (out of 928 hashtags in total) in terms of their purpose of use. All of these hashtags are mentioned in seven tweets or more in our dataset. The results are shown in Table 3 below.

The “percentage” column in the table above denotes the percentage of hashtags in each category among these 100 hashtags that have been coded. The percentage values do not indicate the frequency of the usage of the hashtags. For instance, the first category contains only one hashtag, which is “#article”, accounting for 1% of the hashtags coded. However, “#article” is the most frequently used hashtag among all (which has been used 862 times as is shown in Table 2). The fifth category contains the largest number of hashtags. These research areas range from the simplest categorization of disciplines such as “#science” and “#engineer”, to relatively broad discipline names such as “#biology” and “#neuroscience”, to more specific subareas and topics such as “#cancer”, “#brain”, and “#HIV”. In addition to these, we included three other types of hashtags indicating research areas/topics into this category: those indicating scientists (e.g. “#microbiologist”), science societies (e.g. “#ACS”, the American Chemical Society), and conferences (e.g. “#GI2014”, the Genome Informatics conference). The hashtags in the sixth category are experimental techniques, tools, or objects used. Examples include “#imaging”, “#zebrafish”, “#PCR” (Polymerase Chain Reaction), to name a few. The last category includes three hashtags that we were not able to classify, which are “#reward”, “#motivation”, and “#ethical”.

Frequently mentioned users

In terms of mentions (@), all these tweets contain 1457 mentions of 483 unique accounts. Due to limited space, we present the top 8 mentioned accounts in Table 4. The most highly mentioned account is JoVE (the journal JoVE’s account), which is mentioned 366 times. Evernote’s Twitter account is ranked the second, revealing these Twitter users’ behavior of mentioning @MyEN to save the tweets of the article to their Evernote notes. In addition, two are university accounts, while four are researchers in disciplines related to JoVE’s publication scope.

Similar to our analysis of the hashtags, we coded the top 50 frequently mentioned accounts (out of 483 mentioned accounts in total) to identify their identity. All of these

Table 3 Coding of Top 100 most frequently used hashtags

Code	Percentage (%)
(1) To indicate that this tweet is about an article	1
(2) To indicate that this tweet is about JoVE	3
(3) To emphasize the visual/video feature of JoVE articles	8
(4) To emphasize the technical feature of JoVE articles	4
(5) To specify relevant research areas/topics	69
(6) To specify relevant experimental techniques/tools/objects	10
(7) To promote oneself	2
(8) Others	3

Table 4 Top 8 most frequently mentioned Twitter users

Mentioned User	No.	Coded account identity
@JoVEJournal	366	JoVE the journal
@MyEN	57	Evernote
@ColinW_Bell	18	Research ecologist
@mwallenstein	18	Professor of soil microbial ecology
@crodarte	16	Founder of a health-related company
@Penn	10	University of Pennsylvania
@Uutah	10	University of Utah
@ MicahJMarty	9	Coral reef ecologist

accounts are mentioned in four tweets or more in our dataset. The results are shown in Table 5 below.

In our analysis, institution accounts mentioned is the largest category, containing various types of accounts ranging from universities to departments, to specific laboratories. Other types of research institutions and industrial organizations are also included in this category. One special case is listed in the "Others" category. It is the account of a Protocol Publisher which publishes peer-reviewed scientific protocols (Table 6).

Who tweets JoVE?

As described in the Methods and Data section, in order to gain a deeper understanding of the content included in the tweets and the motivation behind them, we sampled 104 Twitter accounts and 357 tweets for a further content analysis. The following two sections describe the results from this content analysis.

Different from the users mentioned in the tweets, the identity of tweeters shows a different pattern, with the majority of creators of these tweets being individuals and news feeds. All of the news feeds accounts seem to be either Twitter bots or combining bot tweeting techniques with manual tweeting. We looked at the account descriptions, names, and profile photos of the accounts to determine the gender. Among the 43 individual accounts, 29 accounts can be identified as male and 8 as female.

How is JoVE tweeted?

In order to understand how JoVE articles are tweeted, we analyzed the motivation, elements mentioned, and sentiment of the sampled tweets. The occurrence of Video/Visual Elements was also examined.

Table 5 Coding of top 50 most frequently mentioned Twitter users

Code	Percentage (%)
(1) JoVE the journal	2
(2) Evernote	2
(3) Institution	54
(4) Individual	28
(5) News feed	12
(6) Others	2

Table 6 Coding of sampled Twitter accounts

Code	Percentage (%)
(1) Institution	18.3
(2) Individual	41.3
(3) News feed	38.5
(4) Others	1.9

Three major motivation categories are identified in the analysis of the motivation of tweets: dissemination, discussion, and promotion. Tweets coded as "Dissemination" shows an intent of merely distributing the articles. One example of a tweet coded "Here's a video about the STEMO vehicle in Germany. Prehospital Thrombolysis: A Manual from Berlin http://www.jove.com/video/50534/prehospital-thrombolysis-a-manual-from-berlin… #FOAMems #FOAMed". One example from the "Dissemination-Acknowledgement" is "A new paper (and video!) from Paul Race's group explains how to get better protein crystals: http://goo.gl/6tQDBz". Tweets coded as "Discussion" shows personal opinions and potentially the intent to instigate discussions. For instance, "69 soils, 5 enzymes, 4 h. This enzyme assay protocol rocks! http://www.jove.com/video/50961/high-throughput-fluorometric-measurement-potential-soil-extracellular… @ColinW_Bell @mwallenstein" is coded as "Discussion-Commenting". Another example is "Human skeletal muscle biopsy using the modified Bergström technique. Helpful video for training purposes. Sign in at http://www.jove.com/video/51812", which is coded as "Discussion-Learning". Finally, one example of tweets coded as "Promotion" is "My first scientific publication! Shows how video game can improve navigation in blind people http://is.gd/UywBjh #@JoVeJournal #MySciVid".

The results of the coding along with our coding scheme are presented in Table 7 below. If a tweet is created with an intent of distributing an article, it is classified into the category of Dissemination. In this category, normally the main component of the tweet is the title of the article, part of the title, or a summary of the title. As can be seen in the table, the majority of tweets in this category are perfunctory tweets informing the existence of the articles. A small portion of tweets in this category also briefly mention highlights of the articles, which are classified as Dissemination-Acknowledgment. If commenting, relating,

Table 7 Coding of motivation

Code	Percentage (%)
(1) Dissemination	57.7
(1.1) Dissemination-informing	46.5
(1.2) Dissemination-acknowledgment	8.1
(1.3) Dissemination-link Only	3.1
(2) Discussion	24.9
(2.1) Discussion-commenting	14.8
(2.2) Discussion-relating	1.1
(2.3) Discussion-learning	7.3
(2.4) Discussion-conversational	1.7
(3) Promotion	17.4
(3.1) Self-promotion	7.8
(3.2) Other-promotion	9.5

discussion of learning or conversational hints are detected in a tweet, then it is classified into the category of Discussion. Tweets in this category contain comments on both the articles and JoVE the journal. The discussion of learning specific techniques is also found in this category. The Video/Visual Elements are particularly emphasized in 45 (12.6%) of the tweets. Keywords mentioned include “video”, “visualization”, “visual”, “motion”, “illustration”, etc. The category of promotion is assigned to a tweet when the intent of marketing is found in a tweet. Both individual and institution accounts tweet promotional tweets. Institution accounts promote both themselves and their researchers. Researchers tweet articles authored both by themselves and their fellow researchers.

Elements mentioned in the tweets are coded to further illustrate the construction of the JoVE tweets. Our coding scheme and the results of coding are shown in Table 8 below. Title and part of the title are two of the largest categories. When only part of the title is mentioned in a tweet, normally it is the first half of the title. If experimental techniques, tools, objects, or anything related to experimental protocols is mentioned, the tweet is classified into the category of “Methodology of Article”. According to our analysis, Methodology of articles is the third large category mentioned, in almost one-fifth (18.2%) of our sampled tweets.

The sentiment of the tweets indicates whether the Twitter user has a positive, neutral, or negative attitude towards the article mentioned. As is shown in Table 9 below, the majority of tweets are found to be neutral tweets with no obvious positive or negative sentiment. According to our analysis, positive tweets contain positive opinions of not only the JoVE articles but also sometimes the authors, institutes, or disciplines.

Discussion

As mentioned in the introduction section, prior studies have noted the benefits of using scientific videos in scientific research and education. Despite this, the reach and impact of scientific videos, especially peer-reviewed scientific videos, has not been studied. To better understand their reach and impact, it is important to find out whether the tweeters are playing merely a disseminative role or actively trying to elevate the level of discourse and visibility around scientific research and engage in further discussions. The findings also shed light on the interpretation of the impact that tweet counts capture, which is critical to the development and implementation of meaningful altmetrics.

Table 8 Coding of elements mentioned

Code	Percentage (%)
(1) Title	26.3
(2) Part of title	19.0
(3) Summary of title	3.1
(4) Methodology of article	18.2
(5) Conclusion of article	2.2
(6) Concept in article	11.2
(7) Discipline/topic of article	3.4
(8) Summary of article	7.8
(9) Author of article	5.6
(10) Link only	3.1

Table 9 Coding of sentiment

Code	Percentage (%)
(1) Neutral	86.3
(2) Positive	13.2
(3) Negative	0.6

This study sets out with the aim of investigating how video content plays a role in the scholarly communication. This is done by examining communications about peer-reviewed scientific video articles in Tweets. A novel approach for collecting and analyzing the Twitter data is used. Instead of collecting tweets posted by a certain group of researchers or those sharing the same hashtags, we harvested Twitter data by retrieving link citations of these scientific video articles. The tweets "citing" articles from the same journal (JoVE) are not found to be as conversational or topical as normal tweets about scientific articles. However, they exhibit unique and perhaps important features because they are created to communicate a special type of scientific product.

First of all, video/visual elements are highly mentioned in both hashtags and the tweets text. This is an advantage of video publications and could potentially facilitate the online scholarly communication of some disciplines, especially the experimental-oriented physical and life sciences disciplines. The video articles in JoVE are mostly observational and experimental video protocols that could potentially accelerate experimental biological, medical, chemical and physical research. The theme of learning is found in 7.3% of our sampled tweets in our content analysis. This indicates the educational value of these scientific videos to the enhancement of research designs and conducts. Secondly, relating to the first point, a relatively large proportion of tweets are found to mention the methodology of the tweeted articles. This is different compared to previous studies (e.g., Yu et al. 2017). This aspect is particularly important considering the proliferation of false, biased, or irreproducible findings due to methods-related mistakes or inconsistencies in scientific discourse. Thirdly, bots play an important role in disseminating JoVE articles, which is alarming taking findings of previous Twitter bots studies into consideration. Haustein et al. (2016) found at least 9% of tweets to arXiv 2012 submissions published in journals covered by WoS were created by automated accounts. In our study, we find even more in our sampled tweets. The reason behind this is still unclear. However, identifying bots is crucial to avoid misinformation, disinformation, and inflated and potentially incorrect sense of impact in the scholarly communication on Twitter. This remains an important issue in the development of altmetrics. Fourthly, a notable finding emerged regarding the mentions of @MyEN (the EverNote account). By mentioning the @MyEN account in the tweet, it facilitates the user being able to extract and download the thus identified Twitter content into Evernote notes. Thus, it is being used as a citation management mechanism. In the context of this article, we regard the act of tweeting as a means to disseminate or discuss information and consider this to be the primary function of Twitter; however, this secondary by-product of tweeting with a label as a saving behavior for citation management has been observed. This demonstrates the possibility of capturing different types of behavior through digital traces, as left by researchers on a single platform. Additionally, it provides potential interesting and novel ways of studying how researchers' information behaviors have been changed with the advent of new technology. Fifthly, this study illuminates interesting scholarly communication patterns on Twitter by revealing strategies users employ to overcome some of the platforms' limitations, in an effort to instigate deeper, more sophisticated scholarly discourse and discussion. For instance, the frequent use of the "#article" hashtag to communicate JoVE articles indicates that these tweets contain more information than the 140 words limit. Finally, the promotion behavior of different stakeholders has been explored in this study, which provides a good grounding for future studies. It is found that on Twitter, research work of researchers is promoted by institution accounts, their fellow researchers, as well as the researchers themselves.

The purpose of this study is to examine the typical "citing" behaviors of JoVE articles on Twitter. Therefore, considering the extremely skewed distribution of tweets and Twitter accounts, we had to carefully purposefully sample our objects of analysis. After two rounds of pilot studies examining randomly sampled tweets, we only sampled users who have tweeted more than one tweet to reduce the effect of randomness. Considering that our purpose was to understand the tweeting behavior of people instead of bots, we also eliminated three accounts which tweeted more than 20 JoVE articles and were identified by us as Twitter bots. The results of this study are probably not generalizable to other scientific disciplines and other types of research products, although they remain transferable and can serve as a springboard for future research.

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