To Get Cited or Get Tweeted: A Study of Psychological Academic Articles

Abstract

Purpose – By analyzing journal articles with high citation counts but low Twitter mentions and vice versa, this study aims to provide an overall picture of differences between citation counts and Twitter mentions of academic articles.

Design/Methodology/Approach – Citation counts from the Web of Science and Twitter mentions of psychological articles under the SSCI collection were collected for data analysis. An approach combining both statistical and simple content analysis was adopted to examine important factors contributing to citation counts and Twitter mentions, as well as the patterns of tweets mentioning academic articles.

Findings and Interpretations – Compared to citation counts, Twitter mentions have stronger affiliations with readability and accessibility of academic papers. Readability here was defined as the content size of articles and the usage of jargon and scientific expressions. In addition, Twitter activities, such as the use of hashtags and user mentions, could better facilitate the sharing of articles. Even though discussions of articles or related social phenomena were spotted in the contents of tweets, simple counts of Twitter mentions may not be reliable enough for research evaluations due to issues such as Twitter bots and a deficient understanding of Twitter users' motivations for mentioning academic articles on Twitter.

Originality/Value – This study has elaborated on the differences between Twitter mentions and citation counts by comparing the characteristics of Twitter-inclined and citation-inclined articles. It provides useful information for interested parties who would like to adopt social web metrics such as Twitter mentions as traces of broader engagement with academic literature and potential suggestions to increase the reliability of Twitter metrics. In addition, it gives specific tips for researchers to increase research visibility and get attention from the general public on Twitter.

Keywords Scholarly Communication, Altmetrics, Twitter, Twitter metrics, Psychology, Citation

Paper Type Research paper

Introduction

Assessing and evaluating the impacts of scholarly outputs is an essential process in scientific progress and the knowledge advancement of society. Derived from peer-review publishing, citation analysis is the dominant form of scholarly communication and was developed as the primary mechanism for evaluating research (Haustein, Sugimoto and Larivière, 2015).

The development of the Internet has cast new light on traditional scholarly communication. (Gu & Widén-Wulff, 2013). Web 2.0 tools, such as reference managing websites (e.g., Mendeley and CiteULike), wikis, blogs, and social networking sites (e.g., Twitter and Facebook), have sparked faster and less formal methods for scholarly communication and have opened up the boundaries across academia and non-academic communities (Shema, Bar-Ilan & Thelwall, 2012). An increasing number of researchers would like to use the social web to maintain awareness about latest research news and information, disseminate information, interact with diverse audiences, connect with peers in professional networks (Manca and Ranieri, 2016; Veletsianos and Kimmons, 2016; Van Noorden, 2014). Correspondingly, these tools and platforms have yielded broader and timelier impact assessments of scholarly outputs using altmetrics based on social web activities, such as readership, discussions, sharing, and recommendations for a variety of audiences (Fenner, 2014; Das and Mishra, 2014).

Utilizing psychological academic articles as a case study, we examine the differences between citation counts and Twitter mentions in research evaluations. We studied the Twitter mentions of academic articles for the following reasons: 1) Twitter is a primary social media platform used by scientists and researchers (Peoples *et al*., 2016) and 2) the diversity of the Twitter community allows us to draw a comprehensive picture of scholarly communication on the social web, and also the meaning of social web metrics (Barthel *et. al.,* 2015). The field of psychology was selected because it is one of the most popular subjects on social media platforms (Mohammadi and Thelwall, 2014).

The main goal of this study is to better comprehend the role that Twitter plays in scholarly communication, and the value of Twitter mentions in research assessment. It aims to provide useful information to parties including funding agencies, university administrators, and policymakers who would like to adopt social web metrics such as Twitter mentions as traces of broader engagement with academic literature. These traces may be of interest to these parties as the use of academic literature extends beyond the academic community. We also try to encourage and offer tips for researchers to share their research outputs with a larger audience on the social web for higher research visibility and impact.

In this study, starting with a review of existing scholarship examining citation counts, altmetrics, and their determinants, we compared highly-cited and highly-tweeted articles to identify distinct differences between citation counts and Twitter mentions. We first explored how selected attributes including document characteristics, sources, accessibility, wording, and research topics influence differences between citation counts and Twitter mentions. We then investigated the patterns of Tweets citing these academic articles with a simple content analysis approach in which we covered various variables including hashtags, user mentions, and retweets.

Literature Review

Citation counts and altmetrics

The emergence of altmetrics has attracted wide attention from scholars. Altmetrics are regarded as alternative metrics of research evaluations because they make up for the deficiencies of traditional impact assessments; for example, they can handle the most recent publications (Brigham, 2014), they expand the targets of measurements to scholarly works in various formats not limited to written works (Piwowar, 2013), and aggregated altmetrics are able to reflect the achievements of researchers (Mounce, 2013). However, there are some debates regarding the validity of altmetrics. For example, due to the lack of rigorous regulations, cyber-based metrics may not be as reliable as peer-reviewed citations. They can be easily manipulated: for example, "buying" or "selling" posts engagements such as "like" and "share" can lead to a dramatic increase of social web mentions. Moreover, without robust filtering mechanisms or standards, the results of research assessment can be exaggerated due to "spam" posts (Barthel *et al*., 2015). Altmetrics, in use as a type of social web metrics, may also be influenced by heuristics such as authority and bandwagons cues through which the contents posted by authorities and users with many followers are more easily mentioned and disseminated. It is also more likely for social media users to cite their peers' posts (Lee and Sundar, 2013; Lin *et al*., 2016). Stemming from a deficient understanding of the actual meaning of altmetrics, traditional bibliometrics are still the only assessment mechanism of research impacts used by majority of academic institutions (Peoples *et al.*, 2016).

Considerable research has been undertaken regarding correlations between citation counts and social web mentions. A majority of these studies have concentrated on the following questions: whether altmetrics can predict traditional bibliometrics, whether altmetrics can be applied as an impact assessment tool by interested parties, and whether intensive scholarly communication on the social web can lead to higher citation rates.

Based on the analysis of Facebook mentions and citation counts of articles from a variety of disciplines, Ringelhan, Wollersheim, and Welpe (2015) suggested Facebook mentions as an early indicator of the future impact of scientific works according to their positive association. However, they admitted that the validity of the early prediction may differ between disciplines; for instance, the correlation was found to be more significant for psychology articles compared to non-psychology fields such as business and life sciences. Similar results were found in Eysenbach's study (2011), which showed that tweet mentions can predict highly cited articles within the first three days of the publication of scholarly works. He argued that with capacities to measure the social impacts of articles, Twitter metric should be proposed as a supplement to traditional bibliometrics.

These studies have provided inspiring insights into the relationship between citation counts and altmetrics. However, concentrating on correlation testing, some studies may have ignored the fact that these measurements can sometimes be at odds with each other. In addition, the statistical analysis of correlations, either related or not related, is not able to tell the stories hidden under these numerical metrics.

Citations counts, social web mentions, and determinant factors

Citation counts may sometimes fail to reflect the quality or intellectuality of scholarly publications (Gargouri *et al.*, 2010). They were found to be positively related to the accessibility of articles. Taking measures such as making articles open access and the individual or institutional archiving of academic papers increases the number of citation counts (Xia, Myers, and Kay Wilhoite, 2011; Norris, Oppenheim and Rowland, 2008). As mentioned by Didegah and Thelwall (2013), the journal impact factor and the citation impact of referenced articles could be the most effective determinants of citation counts. Besides, an article's internationality and number of authors may determine its citation rate as well. For instance, Gazni and Didegah (2011), through examining the Harvard University affiliated publications between 2000 and 2009, demonstrated that articles involving a larger number of authors and institutions had higher chances of attracting more citations. Taking published research articles from Finland as a case study, Puuska, Muhonen, and Leino (2014) concluded that on top of the impact of the number of authors, international co-publications usually receive more citation counts than domestic collaborations. Similarly, Sin (2011) pointed out that library and information science articles involving international collaborations and authors from high-income nations are more likely to be cited.

Based on 1.3 million Web of Science indexed articles published in 2012, Haustein, Costas, and Larivière (2015) discovered that document characteristics, such as document type, the number of pages, the length of articles, and collaboration patterns, can affect the number of citation counts and social media metrics. For instance, it was found that the number of pages is positively correlated with citation counts but negatively associated with an article's popularity on Twitter, especially in the disciplines of life and earth sciences, math and computer science, social science, and humanities. A longer article title may attract more citation counts but relatively less social media mentions. However, differences existed across disciplines; for example, a longer title led to fewer citations for articles in disciplines such as biomedical and health sciences, natural sciences, and engineering, but brought more citations for articles in social sciences and humanities.

Inspired by the scholarship mentioned above, four main factors, including document characteristics, sources, accessibility, and research topics, were examined in this study in an attempt to attain consistent findings in the field of psychology. We selected articles with incongruent rates of citations and Twitter mentions to clearly visualize the affiliation between relevant factors and the metrics, and also to better understand the differences between citation

counts and Twitter mentions. The comparisons were conducted between articles with incongruent rates of citation counts and Twitter mentions.

Twitter analysis

While previous studies have provided compelling investigations into altmetrics, including Twitter metric, the actual contents of tweets were seldom dissected. To enrich the understanding of Twitter counts, a basic analysis of tweets was utilized in this study to evaluate the meaning of Twitter mentions.

Existing studies related to Twitter analysis have mainly focused on Twitter activities such as the use of hashtags, user mentions (@username), replies, retweets, favorites, including URLs, and so forth. For example, Small (2011) found hashtags in tweets worth exploring because they are keywords assigned to the information, and they provide a summarized description of the contents. According to Small, hashtags can indicate the topics or events embedded in tweets. In a 2016 study by Borgmann *et al.*, the authors examined Twitter discussions on urologic oncology using frequency analysis of words and hashtags in tweet contents, while Naveed *et al.* (2011) took the use of elements such as URLs, exclamations and question marks, and emoticons into account in their Twitter analysis of interestingness. Bruns and Stieglitz (2013) made efforts to develop a set of standardized metrics for Twitter analysis with particular focus on hashtagged exchanges, for instance, counts of tweets sent, counts of original tweets, counts of user mentions sent, counts of genuine replies, retweeted statuses (unedited or edited), unique users, and so on.

We understand that approaches such as sentiment analysis and network analysis are also very popular in Twitter analysis, but due to the limited time and resources, only a basic analysis of Twitter activities such as hashtags, user mentions, and retweets was conducted to discover the patterns of tweets citing academic psychology articles.

Methodology

Extraction of psychological articles and related posts

Psychological articles published between 2012 and 2016 were extracted from Web of Science (WoS) on November 18, 2017. The extraction was based on the International Standard Serial Number (ISSN) of journals under Social Science Citation Index (SSCI) 2015, covering 10 disciplines including applied psychology, biological psychology, clinical psychology, developmental psychology, educational psychology, experimental psychology, mathematical psychology, multidisciplinary psychology, psychoanalysis, and social psychology.

The number of related journals was 587. Articles from WoS were extracted from the Request API for Web of Science Data based on queries combining the above-mentioned ISSNs and publication dates between “2012-01-01” and “2016-12-31” under the SSCI collection. The publication date indexed in WoS refers to “the date on which the records were entered in the product database” (“Web of Science Core Collection Help,” 2017). A total number of 217,768 articles (identified by the accession number “UID” in WoS) were retrieved with their titles, authors, abstracts (if available), publishers, sources, publication dates, page counts, and citation counts. At the same time, we extracted Twitter mention data from Altmetric.com through the Altmetric Explorer by entering the same list of ISSNs and limited the publication period between “2012-01-01” and “2016-12-31” in the advanced search. 568 out of 587 journals and 124,974 articles (identified by item ID) were retrieved. Next, DOI was used as the linkage between WoS records and records from Altmetric.com. Before this, we removed 157 WoS records with duplicate DOIs due to incorrect data entries. Records of 92,435 unique articles (identified by DOIs) were matched. Table 1 shows the number of articles retrieved in each discipline. It is possible for one article or one journal to be classified into more than one category. We used R Studio to process data in this study.

Table 1. Number of articles retrieved from WoS and Altmetric.com

Discipline	Number of Articles indexed in Altmetric.com	Number of Articles indexed in WoS	Number of Articles Matched
Psychology, Biological	4,271	10,586	3,374
Psychology, Clinical	26,307	44,267	19,872
Psychology, Educational	5,549	11,793	4,950
Psychology, Developmental	17,662	26,279	13,516
Psychology, Applied	10,282	20,777	8,700
Psychology, Multidisciplinary	25,809	57,559	20,923
Psychology, Psychoanalysis	870	3,814	597
Psychology, Mathematical	2,022	3,132	1,687
Psychology, Experimental	21,731	42,908	17,771
Psychology, Social	11,647	18,388	10,383

We recognized limitations of the data collection in this study: 1) there are inconsistencies between WoS-indexed articles and those captured by Altmetric.com. For example, not all articles are cross-indexed by both databases. Only successfully matched articles were taken into account in this study. 2) Altmetric.com tracks social web mentions based on identifiers like Digital Object Identifiers (DOI) and URLs ("How it works – Altmetric," 2017). This may lead to a low coverage rate.

Clustering articles based on citations counts and Twitter mentions

To better demonstrate the distinct differences between citation counts and Twitter mentions, we make comparisons between highly-cited and highly-tweeted articles. We targeted articles in the following two clusters: 1) Citation-inclined: articles with high citation counts captured by WoS but low Twitter mentions. 2) Twitter-inclined: articles with high Twitter mentions but low citation counts.

As Twitter mentions and citation counts were found to be heavily affected by recency (date of publication) and research disciplines (Zahedi*, et. al.,* 2014; Hammarfelt, 2014), in order to investigate articles in different disciplines and those that were published in different years, normalization was applied to Twitter mentions and citations separately in each discipline and publication year. The formula $((i - 0.5)/n*100)$ used in the study of Bornmann and Haunschild (2016) was adopted for the calculation of percentiles; i is the integer value of rank position (ascending) of an article in the set of articles within the same discipline and published in the same year, while n refers to the total number of articles in the set. If an article is classified into m number of disciplines, we divided the sum of percentiles by m to get an average percentile. We used Avg Tp to represent average Twitter mention percentile and Avg Cp to represent average citation count percentile.

According to the 80/20 scientometric data quality rule (Strotmann and Zhao, 2015), bibliometric data needs to have at least 80% coverage in the database to allow a reliable field-specific study. Therefore, before data normalization, we excluded sets of publications in each discipline and publication year in which over 20% of articles received zero mention on Twitter (see Table 2). The number of remaining unique articles was 49,150.

Table 2. Twitter coverage of publications by discipline and publication year

Discipline	**2012 %**	**2013 %**	**2014 %**	**2015 %**	**2016 %**
Psychology, Applied	56.03	71.91	77.66	79.08	88.04
Psychology, Biological	60.28	69.37	76.12	86.52	94.99
Psychology, Clinical	69.12	77.7	79.76	83.53	91.02
Psychology, Developmental	71.57	79.05	83.72	89.17	92.25
Psychology, Educational	58.78	70.53	76.49	83.3	89.64
Psychology, Experimental	54.77	67.71	74.82	79.62	90.14
Psychology, Mathematical	44.65	62.88	67.35	74.21	86.29
Psychology, Multidisciplinary	68.87	78.84	82.05	86.67	89.97
Psychology, Psychoanalysis	85.19	75.76	83.56	71.62	67.46
Psychology, Social	72.29	81.25	83.64	84.57	90.60

We classified an article with an Avg Cp above the 70th percentile but an Avg Tp below the 30th percentile as citation-inclined, while an article with an Avg Tp above the 70th percentile but an Avg Cp below the 30th percentile was classified as Twitter-inclined. We selected the 70th and 30th percentiles as thresholds for the following reasons: 1) the difference between the Avg Cp and Avg Tp makes the articles in citation-inclined and Twitter-inclined clusters distinctive; 2) this allowed us to keep a relatively large and balanced set of articles that provided a higher level of accuracy in data analysis. In this way, 3,536 articles (7.19%) and 3,026 articles (6.16%) were respectively classified as Twitter-inclined and citation-inclined articles (see Figure 1).

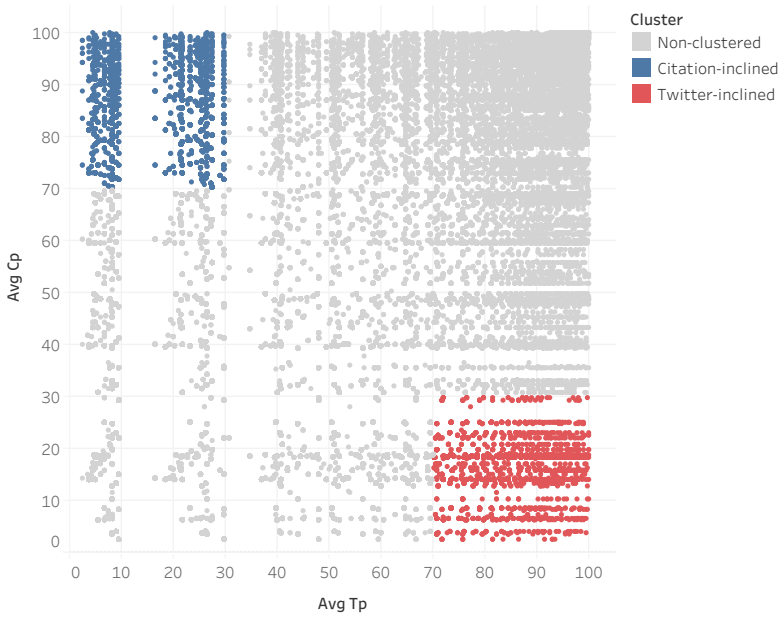

Figure1. Clustering Articles Based on the 70th and 30th Percentiles of Citation Counts and Twitter Mentions

As shown in Table 3, articles in the Twitter-inclined cluster had been mentioned at least 3 times on Twitter, while the most-tweeted articles had been mentioned 695 times on Twitter. Regarding citation counts of Twitter-inclined articles, the range was between 0 and 4. The

citation counts among citation-inclined articles fell between 3 and 114, while the Twitter mentions ranged from 0 to 2.

Table 3. Descriptive statistics (citation counts and twitter mentions) of clustered articles

Cluster		mean	median	max	min
Twitter-inclined (3,536 articles)	Twitter mention	15.67	10	695	3
	Citation count	0.5	0	4	0
Citation-inclined (3,026 articles)	Twitter mention	0.81	1	2	0
	Citation count	10.13	7	114	3

In order to better comprehend Twitter mentions, we extracted tweets mentioning Twitter-inclined articles from Altmetric.com. Information retrieved included the username of the tweet author, publication data and time, tweet ID, and tweet contents. The number of tweets collected was 47,146. We further utilized the Twitter API for Python to gather additional details of the tweets. Matching with tweet IDs, Twitter API provides information such as tweet contents, users involved, interactions (i.e. retweet, reply, and quote), geolocations, and etc. In this study, retweeted status ("retweeted_status"), quoted status ("quoted_status"), user mentions ("user_mentions"), and hashtags ("hashtags") were retrieved. Since some of the tweets had been deleted by their authors, only 32,394 tweet records were successfully retrieved and used in our data analysis.

Data analysis

Article Attributes Affiliated with Citation Counts and Twitter Mentions

Four main attributes, including document characteristics, source, accessibility, and the topics and wording of article titles and abstracts, were used for analysis (see Table 4). Statistical analysis was utilized to test the correlations between the above-mentioned variables and the clustering of articles. A chi-squared test was used for categorical variables and an independent sample t-test was used for numerical variables.

Table 4. Article Attributes

Main Attribute	Sub-attribute	Measurement
Document Characteristics	Number of authors	**Numerical Variable**
	Length of title (word counts)	**Numerical Variable**
	Length of abstract (word counts)	**Numerical Variable**
	Number of pages	**Numerical Variable**
Source	Journal Impact Factor (JIF)	**Numerical Variable**: Average JIF percentile retrieved from WoS Journal Citation Report 2015. Average JIF percentile is a percentile value reflecting the rank of journals by JIF within their subjects, and hence it allows cross-subject comparisons ("Average Journal Impact Factor Percentile," 2017). A journal with an average JIF percentile higher than 75 means it is in the top 25% of journals within its research areas.
Accessibility	Open access status	**Binary Variable**: Open Access or Non-Open Access Since the open access status is not available from WoS API, we imported the DOI list of selected articles into the WoS database for information extraction. The open access information provided by WoS refers to gold open access in which the authors pay publishers specific processing charges to publish their articles with free access.

Table 4. Article Attributes (Cont.)

Research Topic and Wording	We extracted featured terms from both citation-inclined and Twitter-inclined articles. Based on the occurrences of featured terms, we attempted to attain a preliminary understanding of the topics covered by the selected articles and their patterns of wording, e.g., how the ideas and messages were expressed and conveyed. Using the pre-processed text of titles and abstracts, we created a binary document-term matrix based on the occurrences of terms in each article. To identify terms affiliated with citation counts and Twitter mentions, we calculated the normalized distance (numeric variable: NormDist) between the Avg Tp and Avg Cp for each article i (see the formulas below). The range of NormDist is between 0 and 1. Accordingly, NormDist closer to 1 refers to a higher degree of Twitter inclination while citation-inclined words will get the lowest value of NormDist. Accordingly, a higher value of Dist reflects a higher degree of Twitter-inclination, while a lower value of Dist represents a higher level of citation-inclination. $Dist_i = Avg\ Tp_i - Avg\ Cp_i$ $NormDist_i = (Dist_i - \min(Dist))/(\max(Dist)-\min(Dist))$ T-tests were employed to examine the correlations between the occurrence of each word, namely whether the word was presented in the articles, and the articles' level of inclination reflected by NormDist. Words were excluded if they occurred less than 50 times in all articles, or there was no statistical significance shown in the above-mentioned t-tests ($p>=0.01$). We classified words whose occurrences leading to the highest and lowest means of NormDist among the articles respectively as Twitter-inclined and citation-inclined words. The top 50 Twitter-inclined terms and top 50 citation-inclined terms were selected as featured terms.

Patterns of Twitter Mentions

In order to better comprehend Twitter mentions, we conducted basic analysis of tweet contents that mentioned selected articles. Table 5 shows how we defined relevant attributes in this study.

Table 5. Identifying Patterns of Tweets

Attribute	Measurement
Hashtags	**Binary Variable:** whether the article was mentioned with hashtags
User mentions	**Binary Variable:** whether the article was shared with user mentions
Retweet	**Binary Variable:** whether the tweet is a retweet (either retweet or quote tweet, which refers to a retweet with comments). We did not analyze quote tweets separately because this feature was introduced in 2015 (Griffin, 2015) and, hence, the status of tweets before this launch may not be properly captured. **Numeric Variable:** number of tweets retweeting the tweet

By presenting sample tweets, we made further interpretations on users' Twitter activities where psychological academic articles were mentioned, e.g., the top hashtags based on their occurrences in Tweets, the way hashtags were used in tweets, the patterns of the most popular tweets based on the number of retweets, and so forth. Through this, we tried to demonstrate the diversity of user patterns in communication and interactions. Lastly, we added a section to share explorative findings during our studies as well to provide more ideas about tweets and Twitter metric.

Findings and Discussion

Article Attributes Affiliated with Citation Counts and Twitter Mentions

In this section, we compare articles in Twitter-inclined and citation-inclined clusters to identify potential attributes that are affiliated with the traditional counts and Twitter mentions of academic articles.

1) Document characteristics

Firstly, the content size of articles is found to be an important factor contributing to the Twitter inclination of articles. Articles with less pages and shorter titles and abstracts seem to have higher chances of becoming highly-tweeted. In contrast, articles with longer titles and abstracts and more pages are more appealing to citation counts. These mean differences (see Table 6) are all significant at 0.01 level. For example, the average length of abstracts of Twitter-inclined articles is 150.80, while, for the citation-inclined articles, the mean is 172.02. Twitter-inclined articles also tend to have shorter titles and contents. Regarding the number of authors, citation-inclined articles are more likely to have more authors (4.12 authors on average) than Twitter-inclined articles (3.47 authors on average). This mean difference is significant at 0.01 level.

Table 6. Document characteristics: Mean differences between Twitter-inclined and citation-inclined articles

Attribute	Mean in citation-inclined cluster	Mean in Twitter-inclined cluster
Length of title (word counts) $t = 5.63$, $p < 0.01$	14.03	13.56
Length of abstract (word counts) $t = 14.07$, $p < 0.01$	172.02	150.80
Number of pages $t = 10.05$, $p < 0.01$	12.78	11.33
Number of authors $t = 10.64$, $p < 0.01$	4.12	3.47

2) Impacts of source

The impacts of journals were reported to have a strong correlation with citation counts (Didegah and Thelwall, 2013). This conclusion can also be applied to Twitter mentions, according to our study. Figure 3 shows that around 85% of citation-inclined articles and over 74% of Twitter-inclined articles were published in journals in Quartile 1 and Quartile 2 (Average JIF Percentile between 50 to 100). However, generally, the impacts of journals may have stronger affiliation with citation counts. The mean of average JIF percentiles of citation-inclined articles is 71.65%, while for Twitter-inclined articles, the mean of average JIF percentiles is 64.65%. The mean difference is significant at 0.01 level in t-test ($t = 13.29$, $p < 0.01$).

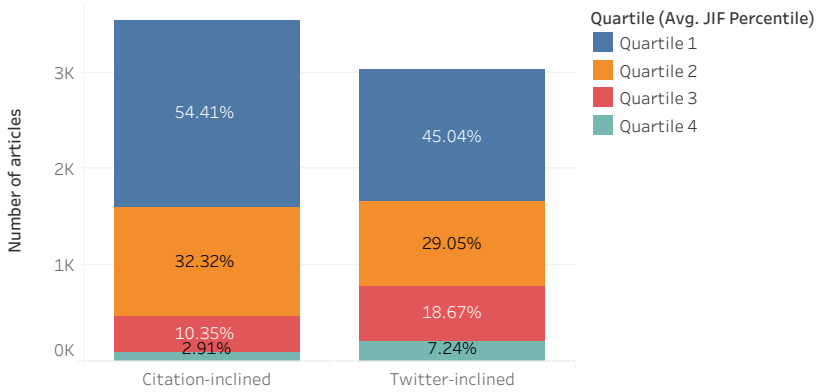

Figure 2. Distribution of Clustered Articles by Quartiles of Average JIF Percentile

3) Accessibility

Compared to citation counts, accessibility drives more Twitter mentions. In our study, 12.46% of Twitter-inclined articles are open access articles. This percentage is higher than that of citation-inclined articles (3.48%) and higher than the percentage of open access articles among all selected articles (7.62%). This difference is significant at 0.01 level in chi-squared test (x^2=160.24, $p < 0.01$).

Accessibility is a very important precondition for article dissemination and discussion on social web platforms such as Twitter. Twitter users outside of academia may have very limited access to non-open access articles, let alone the ability to share them with others. However, this may not be a critical problem for scientists affiliated with universities or research institutes, which should provide them accessible resources for research including subscription-based articles.

4) Research topic and wording

The feature words extracted indicate a similar finding: articles with jargon and scientific expressions are less likely to be Twitter-inclined. For example, as shown in Figure 2, highly-tweeted articles have less jargon compared to highly-cited articles, e.g., "sct" (sluggish cognitive temp), "nssi" (non-suicidal self-injury), "dsm" (Diagnostic and Statistical Manual of Mental Disorders), "comorbidity," and so forth. In addition, theory or methodology-related terms are more likely to appear in citation-inclined articles, e.g., "bifactor," "discriminant," "validity," "confirmatory," "conceptualization," "narcissism," etc.

Twitter mentions seem to have a close affiliation with topics related to sex and gender (represented by terms such as "infidelity," "heterosexual," "mating," and "sexuality"), developmental disorders (e.g., "autistic," "autism"), crime and violence (e.g., "crime," "victim," "violent"), and so on.

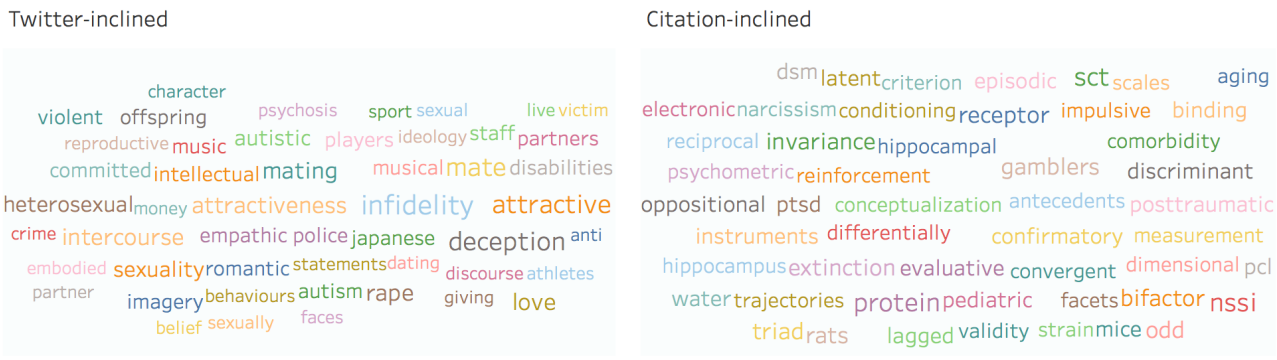

Figure 3. Top 50 featured words in Twitter-inclined and citation-inclined clusters

A potential explanation of these differences could be the diversity of Twitter users. Twitter users from the general public may not have the strong knowledge backgrounds of researchers and scientists that allow them to understand academic theories or methodologies in articles. Hence, they tend to selectively absorb and share information or knowledge which is easier to understand on the Internet. This can be regarded as a weakness of Twitter mentions because they may be biased against articles with academic or scientific expressions, such as academic concepts and experimental methods. Moreover, they have strong preferences towards particular topics. This could also be a reason why certain highly-cited articles within academia have failed to arouse wide discussions on the social web.

Patterns of Twitter Mentions

In this section, we examined tweets mentioning Twitter-inclined articles with the purpose of understanding patterns hidden behind the numeric counts.

1) Twitter Activities

Hashtags and user mentions were found to have positive correlations with the number of Twitter mentions. Among Twitter-inclined articles, articles assigned with at least one hashtag when mentioned on Twitter received 18.32 mentions on average, while those mentioned without hashtags received 11.55 mentions on average ($t = 4.09$, $p<0.01$). In terms of user mentions, articles shared without any Twitter handle or username received 7.15 Twitter mentions, while those that mentioned other users had higher Twitter mentions with 16.23 on average ($t = 4.13$, $p <0.01$). Both mean differences are significant at 0.01 level.

Figure 4 shows hashtags that occurred at least 10 times in the tweets mentioning Twitter-inclined articles. The size of the circles reflects the number of tweets. Hashtags that occurred together are represented by links, while the thickness of the links refers to the number of times the hashtag occurred. Most of these hashtags represent the topics of articles, and they also show that topics such as mental health (e.g., #mentalhealth, #depression, #PTSD, and #anxiety), developmental disorders (e.g., #autism), family violence (e.g., #childabuse), and sex and gender (e.g., #LGBT, #sexual, and #HIV) are relatively popular among Twitter users. In addition, Twitter users may assign generic tags such as "#psychology" and "science" together with the topics of articles.

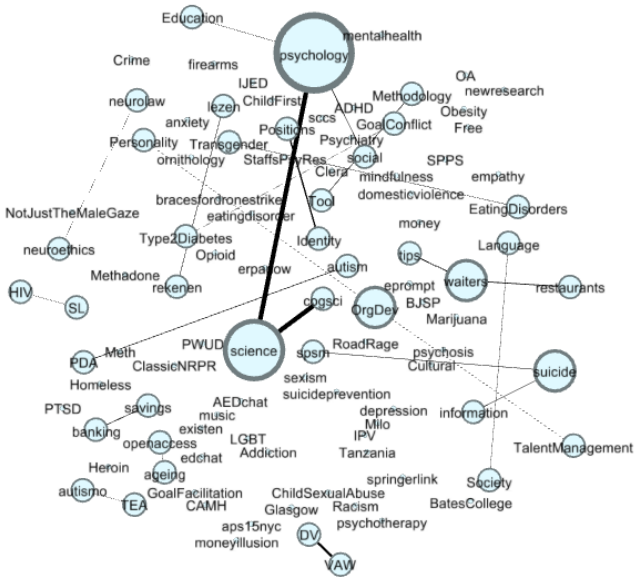

Figure 4. Top hashtags in tweets mentioning Twitter-inclined articles

Another interesting pattern among these hashtags is the mention of open access status (e.g., #openaccess, #Free, and #OpenAccess). These Twitter users could be researchers, publishers, universities, research institutes, and others. By sharing the academic articles with others, these Twitter users intended to announce the release of their publication and to attract the audience on Twitter. Below are three example tweets; the first is a tweet shared by the department of psychology of a university, the second tweet was posted by a scientific publisher, and the third tweet was shared by a research fellow working in a research institute of a university.

"Our department has published a new paper on maternal cognitions and principles #openaccess http://t.co/xxxxxx"
"#openaccess in our journal: research article on #autism #PDA http://t.co/xxxxx"
"Our #review paper on in #cats! #OpenAccess #communication https://t.co/xxxxx"

In addition, publishers (e.g., #springerlink and #IJED) are highlighted in the form of hashtags. It is interesting that not only publishers added themselves as hashtags in their tweets in order to announce new publications, researchers and practitioners also tagged publishers when they share academic articles on Twitter. For example, an associate professor in the field of speech language pathology wrote: "I'm reading this on https://t.co/xxxxx #springerlink." Another example is from a Juris doctoral student, sharing his first journal article with the following tweet: "My first journal article has just been published! https://t.co/xxxxx #springerlink." These tweets were probably modified based on tweet templates from journal websites. For instance, the tweet template for Springer journals is "the title of article + URL of the article + #springerlink."

It is also common among Twitter users to mention other users when sharing articles on Twitter. For example, some users would like to mention the authors in their post, such as "A preregistered replication study of a classic psychological theory [...] http://t.co/xxxxxxxxx from @username", "An interesting replication attempt by @username and @username. http://t.co/xxxxxxxxx" and "Congratulations to our lecturer @username on her latest publication http://t.co/xxxxxxxx". Twitter mentions were also used to alert others to the article, for instance, "[...] This is a possible explanation for gender paradox [...]@username" and "@username This is an interesting paper! http://t.co/xxxxxxxx". Twitter users may use user mentions to relate the article to other relevant users as well. For instance, a professor of psychology mentioned another professor in the same research area in his post "[...] Robot-enhanced psychotherapy works [...] http://t.co/xxxxxxxxx @username is crying tears of joy".

2) Retweets

We observed that 56.78% of tweets mentioning Twitter-inclined articles are retweets. And due to Twitter's character limit, contents posted by Twitter users were quite straightforward. Most of these top tweets simply highlighted the findings of articles or posted short comments about articles or related social phenomena with additional URLs. The patterns of the top 10 most retweeted English-written tweets are listed in Table 7. Firstly, these top tweets were posted by various types of users, such as a literature recommendation page that mainly shares the latest studies, including academic articles, in specific research disciplines, researchers or scientists (e.g., professors and research fellows), scientific publishers, other professionals (e.g., software engineers), and members of the general public (e.g., bloggers). This finding is consistent with the diverse user community of Twitter.

Table 7. Top 10 most retweeted English-written tweets

Tweet author	Tweet content pattern	Topics	Number of retweets
Literature recommendation page	summary of the article + URL of the article + screenshot of the abstract	Gender stereotypes and socialization	229
Professor of sociology	highlights of research findings + URL of the article	Racism and internet	167
Postdoctoral fellow of psychology	comments on the article ("this article has addressed a huge gap in the scientific literature") + URL of the article + screenshot of highlighted contents	Psychological characteristics of professionals	167
Software engineer	highlights of research findings + URL of the article	Feminism	165
Professor of psychology (1)	discussion on social phenomenon based on findings of the article + URL of the article	Gender stereotypes and socialization	93
Scientific publisher	quote from the article + URL of the article	Education and psychology	92
Blogger	summary of research finding to support personal view + URL of the article	Human evolution	88
Literature recommendation page (2)	highlights of research findings URL of the article + screenshot of highlighted contents	Racial microaggressions and psychotherapy	70
Professor of psychology (2)	comments on the articles ("amusing and plausible") + URL of the article	Feminism	69
Professor of developmental psychopathology	highlights of research findings + URL of the article	Autism	68

Additional explorative findings

1) Replies to tweets

Even though the tweets mentioning psychological academic articles may not involve in-depth discussions, we noticed some interesting discussions and interactions between Twitter users, especially in replies to tweets. In order to tell a diverse story, we showed below some examples of replies to the top retweeted tweets mentioning psychology articles. We understand that without systematic sampling or text clustering analysis, the replies covered in this section are not completely representative.

The first three replies question the research methods of the articles, while the fourth example refers to the research gap. In other words, we may assume that scholarly discussions do exist among Twitter mentions, though we did not study their motivations of the sharing further. It is also evident that Twitter users link real-life phenomena or their personal views with the academic articles mentioned on Twitter (see the 5th, 6th, and 7th examples).

"Would there be any value in performing the same study using men?"

"Their sample size is too small […] This really needs replication."

"it is a persuasive argument […] but it seems to be post-hoc […]"

"still massive gap for studies on non-Italian clowns […]"

"[…] does that mean we should teach children with autism to read using the whole word rather phonics method […]"

"[…] We do not understand why you, as a professional, consider autism to be a disorder […]"
"[…] I find it insulting to be told I'm (as a female) weak enough to be oppressed."

2) Issue of Twitter bots

Consistent with previous studies (Barthel et al., 2015), we are aware of the Twitter bots among the Twitter mentions that we examined in this study. Ferrara et al. (2016) demonstrated that a significant difference between human accounts and bot accounts is that bots tend to retweet more than human accounts, while by contrast, human accounts usually receive more balanced interactive engagements, such as replies, mentions, and retweets. In accordance with this, we attempted to identify suspects by the imbalance between their activities and user engagements that they received.

For instance, we plotted the number of tweets mentioning selected psychological articles by Twitter accounts to represent the level of activity and the number of selected tweets being retweeted to reflect the engagements which they attained in Figure 5. It is apparent that the three accounts circled on the left of the chart were considerably active regarding the number of tweets. However, their tweets were seldom retweeted. In other words, these accounts may have received very limited responses from other Twitter users. Additionally, we happened to find that three of them were linked together with the account highlighted on the right, with almost all of their posts were shared at the same time with the same content. When looking into the content of the tweets, a majority of their posts attempted to share publications including academic books and articles related to the topics of HIV, sex workers, and prison health from different publishers. Without concrete evidence, we cannot determine the actual purpose of these posts, but we have to admit that suspicious accounts like these may partly pollute the Twitter mentions, as well as their validity and reliability in measuring impacts.

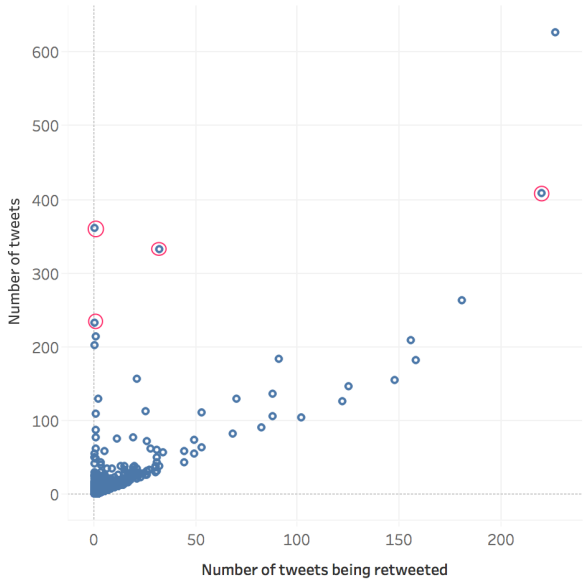

Figure 5. Number of tweets vs. Number of tweets being retweeted by Twitter accounts

Limitations

There are some limitations in this study. First, only psychology articles and Twitter were taken for analysis. The findings may be different when the focus is shifted to other disciplines or platforms with different demographics. Second, this study only covered articles indexed by the Web of Science and Altmetric.com, while articles without valid web identifiers were

ignored. Additionally, this study lacks an analysis of interactions among Twitter users and of their motivations for scholarly communication on the social web.

Conclusion

Comparisons between Twitter-inclined and citation-inclined articles showed the "preferences" of citation counts and Twitter mentions. Twitter mentions were found to be closely affiliated with the readability of articles, defined as the content size (length of the article, abstract, and title) and the usage of scientific jargon, and the accessibility of articles. This may be attributed to the diverse audience on Twitter, as some Twitter users may not have the background to understand jargon or academic theories. Twitter mentions were "picky" towards specific article topics. In contrast, citation counts were friendly to articles with longer titles and abstracts, a larger number of pages, and those that placed greater emphasis on scientific theories and methodologies. In this sense, both Twitter mentions and citation counts may not perfectly reflect academic or other impacts of articles.

We noticed other weakness of Twitter mentions in this study. However, though this study did not provide a profound interpretation of the meaning of Twitter metrics, the great potentials of Twitter metric in measuring the broader engagement of scholarly outputs other than academic values in the strict sense should be recognized. One reason is that we observed a variety of users and audience involved in the article sharing on Twitter, e.g., academic researchers, research institutions, publishers, professional practitioners, members from the general public and so on. Moreover, discussions towards the articles exist though they may not be very rigorous or insightful. For example, as shown in this study, Twitter users may recommend interesting articles, question the methodology of the mentioned articles, summarize research gaps, link real-life experiences with academic articles and so forth. To enhance the reliability of Twitter metrics, we suggest the following measures as potential solutions: 1) in addition to the number of tweets, the engagement of Twitter users should be analyzed to reflect the popularity of articles on Twitter. For example, in our study, the contents of replies seem to be very informational and sometimes more comprehensive than the original tweets. Unfortunately, these interactions were not analyzed in this study. Future studies can explore the possibility of adopting social network analysis to measure the impacts of articles on Twitter. 2) It is necessary to use filtering algorithms to identify Twitter bots and spam posts because they have the power to dramatically increase Twitter mentions. For instance, the suspicious accounts spotted in this study "contributed" over thousands of Twitter mentions combined. 3) It would be useful to apply sentiment analysis to tweets, since some tweets actually criticize the articles rather than favoring them.

Twitter activity may increase the odds of Twitter mentions. Hence, we encourage researchers to engage with a larger audience including research peers, industrial practitioners, and also the general public on Twitter or other social platforms. While we are not certain about the kind of impact that can be reflected by Twitter metric, sharing scholarly output on the social web can improve knowledge exchange and also promote the transformation of academic knowledge to technological and societal advancement. Below are some practical tips for researchers who would like to share their research outputs on Twitter or other social media platforms:

1) Increase the accessibility of articles by publishing open access. If there is not enough funding to support gold open access, an alternative way to increase the visibility of scholarly outputs is through self-archiving or depositing appropriate versions (e.g., preprints or postprints) into open repositories.
2) Tag articles with relevant research topics, and try to adopt tags commonly used by other researchers or online communities.
3) Link articles with related social phenomena or industrial trends that resonate with the general public.

4) When mentioning or sharing academic articles on the social web, try to translate them into simple messages, e.g., avoiding excessive use of jargon and summarizing important contents for diverse audiences.

References

Barthel, S., Tönnies, S., Köhncke, B., Siehndel, P. and Balke, W.-T. (2015), "What does Twitter Measure?", *Proceedings of the 15th ACM/IEEE-CE on Joint Conference on Digital Libraries - JCDL '15*, ACM Press, New York, New York, USA, pp. 119–128.

Borgmann, H., Loeb, S., Salem, J., Thomas, C., Haferkamp, A., Murphy, D.G. and Tsaur, I. (2016), "Activity, content, contributors, and influencers of the twitter discussion on urologic oncology", *Urologic Oncology: Seminars and Original Investigations*, Vol. 34 No. 9, pp. 377–383.

Bornmann, L. and Haunschild, R. (2016), "How to normalize Twitter counts? A first attempt based on journals in the Twitter Index", *Scientometrics*, Vol. 107 No. 3, pp. 1405–1422.

Brigham, T.J. (2014), "An Introduction to Altmetrics", *Medical Reference Services Quarterly*, Vol. 33 No. 4, pp. 438–447.

Bruns, A. and Stieglitz, S. (2013), "Towards more systematic Twitter analysis: Metrics for tweeting activities", *International Journal of Social Research Methodology*, Vol. 16 No. 2, pp. 91–108.

Das, A. and Mishra, S. (2014), "Genesis of altmetrics or article-level metrics for measuring efficacy of scholarly communications: Current perspectives", *Journal of Scientometric Research*, Vol. 3 No. 2, p. 82-92.

Didegah, F. and Thelwall, M. (2013), "Determinants of research citation impact in nanoscience and nanotechnology", *Journal of the American Society for Information Science and Technology*, Vol. 64 No. 5, pp. 1055–1064.

Eysenbach, G. (2011), "Can tweets predict citations? Metrics of social impact based on Twitter and correlation with traditional metrics of scientific impact", *Journal of Medical Internet Research*, Vol 13 No. 4, e123.

Fenner, M. (2014), "Altmetrics and other novel measures for scientific impact", in Bartling, S. and Friesike, S. (Eds), *Opening Science: The Evolving Guide on How the Internet is Changing Research, Collaboration and Scholarly Publishing*, Springer, Heidelberg, pp. 179-189.

Ferrara, E., Varol, O., Davis, C., Menczer, F. and Flammini, A. (2014), "The Rise of Social Bots", *Communications of the ACM*, Vol. 59 No. 7, pp. 96–104.

Gargouri, Y., Hajjem, C., Lariviére, V., Gingras, Y., Carr, L., Brody, T. and Harnad, S. (2010), "Self-selected or mandated, open access increases citation impact for higher quality research", *PLoS ONE*, Vol. 5 No. 10, p. e13636.

Gazni, A. and Didegah, F. (2011), "Investigating different types of research collaboration and citation impact: A case study of Harvard University's publications", *Scientometrics*, Vol. 87 No. 2, pp. 251–265.

Griffin, A. (2015), "Feature has been gradually rolled out to some users, but was officially unveiled in a tweet this morning", *Independent*, 7 April 2015, available at: http://www.independent.co.uk/life-style/gadgets-and-tech/news/twitter-launches-retweet-with-comment-lets-users-quote-tweets-without-wasting-characters-10159587.html (accessed 17 Nov 2017).

Gu, F. and Widén-Wulff, G. (2011), "Scholarly communication and possible changes in the context of social media: a Finnish case study", *The Electronic Library*, Vol. 29 No. 6, pp. 762–776.

Hammarfelt, B. (2014), "Using altmetrics for assessing research impact in the humanities", *Scientometrics*, Vol. 101 No. 2, pp. 1419–1430.

Haustein, S., Costas, R. and Larivière, V. (2015), "Characterizing social media metrics of scholarly papers: the effect of document properties and collaboration patterns", *PloS ONE*, Vol. 10 No. 3, p. e0120495

Haustein, S., Sugimoto, C. and Larivière, V. (2015), "Guest editorial: social media in scholarly communication", *Aslib Journal of Information Management*, Vol. 67 No. 3.

Lee, J.Y. and Sundar, S.S., 2013. "To tweet or to retweet? That is the question for health professionals on Twitter". *Health Communication*, 28(5), pp.509-524.

Lin, X., Spence, P.R. and Lachlan, K.A., 2016. "Social media and credibility indicators: The effect of influence cues". *Computers in Human Behavior*, 63, 2016, pp.264-271.

Xia, J., Myers, R.L. and Wilhoite, S.K. (2011), "Multiple open access availability and citation impact", *Journal of Information Science* , Vol. 37 No. 1, pp. 19-28.

Manca, S. and Ranieri, M. (2016), "Yes for sharing, no for teaching! Social media in academic practices", *The Internet and Higher Education*, Vol. 29, 2016, pp. 63-74.

Mohammadi, E. and Thelwall, M. (2014), "Mendeley readership altmetrics for the social sciences and humanities: Research evaluation and knowledge flows", *Journal of the Association for Information Science and Technology*, Vol. 65 No. 8, pp. 1627–1638.

Mounce, R. (2013), "Open access and altmetrics: Distinct but complementary", *Bulletin of the American Society for Information Science and Technology*, Vol. 39 No. 4, pp. 14–17.

Naveed, N., Gottron, T., Kunegis, J. and Alhadi, A.C. (2011), "Bad news travel fast", *Proceedings of the 3rd International Web Science Conference on - WebSci '11*, ACM Press, New York, New York, USA, pp. 1–7.

Norris, M., Oppenheim, C. and Rowland, F. (2008), "The citation advantage of open access articles", *Journal of the American Society for Information Science and Technology*, Vol. 59 No. 12, pp. 1963-72.

Peoples, B.K., Midway, S.R., Sackett, D., Lynch, A. and Cooney, P.B. (2016). Twitter predicts citation rates of ecological research. *PloS one*, Vol. 11 No. 11, p. e0166570.

Piwowar, H. (2013), "Altmetrics: Value all research products", *Nature*, Vol. 493 No. 7431, p. 159.

Puuska, H.M., Muhonen, R. and Leino, Y. (2014), "International and domestic co-publishing and their citation impact in different disciplines", *Scientometrics*, Vol. 98 No. 2, pp. 823–839.

Ringelhan, S., Wollersheim, J. and Welpe, I.M. (2015), "I like, I cite? Do Facebook likes predict the impact of scientific work?", *PLoS ONE*, Vol. 10 No. 8, p. e0134389.

Shema, H., Bar-Ilan, J., & Thelwall, M. (2012). Research blogs and the discussion of scholarly information. *PloS one*, 7(5), e35869.

Sin, S.C.J. (2011), "International coauthorship and citation impact: a bibliometric study of six LIS journals, 1980-2008", *Journal of the American Society for Information Science and Technology*, Vol. 62 No. 9, pp. 1770-1783.

Small, T.A. (2011), "What the hashtag?: A content analysis of Canadian politics on Twitter", *Information Communication and Society*, Vol. 14 No. 6, pp. 872–895.

Strotmann, A. and Zhao, D. (2015), "An 80/20 Data Quality Principle for Professional Scientometrics?", *Proceedings of ISSI 2015—15th International Society of Scientometrics and Informetrics Conference*, Istanbul, June 29-July 3 2015.

Van Noorden, R. (2014), "Online collaboration: scientists and the social network", *Nature*, Vol. 512 No. 7513, pp. 126-129.

Veletsianos, G. and Kimmons, R. (2016). Scholars in an increasingly open and digital world: How do education professors and students use Twitter?. *The Internet and Higher Education*, Vol. 30, pp.1-10.

Zahedi, Z., Costas, R. and Wouters, P. (2014), "How well developed are altmetrics? A cross-disciplinary analysis of the presence of 'alternative metrics' in scientific publications", *Scientometrics*, Vol. 101 No. 2, pp. 1491-1513.

"Average Journal Impact Factor Percentile". (n.d.)., available at: http://ipscience-help.thomsonreuters.com/incitesLiveJCR/glossaryAZgroup/g4/9995-TRS.html (accessed 18 May 2017)

"How it works – Altmetric". (n.d.)., available at: https://www.altmetric.com/about-our-data/how-it-works/ (accessed 4 June 2017).

"Web of Science Core Collection Help". (n.d.)., available at: http://images.webofknowledge.com/WOKRS5251R3/help/WOS/hp_advanced_search.html (accessed 4 June 2017).