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Direct and Indirect Influence of Altmetrics on Citation in Social Systems: Assessing a New Conceptual Model

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Abstract

This study aimed to assess the paths through which save metrics (on CiteULike, Mendeley, and Figshare) and discussion metrics (on Twitter, Facebook, and Wikipedia) influence citation. This descriptive-correlation study investigates the relationships between different variables based on its proposed conceptual model. Systematic and stratified sampling was employed and, using the Cochrane formula, the sample size was determined to be 1892 articles. Data were collected using the PLOS altmetrics, and path analysis was administered to test the conceptual model by using AMOS software. The results convey that Mendeley was the most effective path resulting to citation. Mendeley has a positive and significant relationship with citation via save as an intermediator. Twitter also had a negative and significant relationship with citation via discussion as an intermediating factor. Yet, neither save metrics on CiteULike and Figshare nor discussion on Facebook and Wikipedia does create a path of influence on citation. Identifying the effective paths through which social networks affect citation via altmetrics and presenting a final model of those paths could enrich and expand the theoretical foundations in the field of altmetrics. Besides identifying the most effective social networks and paths for online scientific interactions that lead to citation, the implications of this research can provide deeper insights for policy makers, editors and scholars.

Keywords: Altmetrics, Visibility, Citation, Save Metrics, Discussion, Pathway, Path Analysis, PLOS System, Intermediation, Mendeley, CiteULike, Figshare, Twitter, Facebook, Wikipedia.

Introduction

Scientific references constitute the most objective manifestation of the use of informational sources in scientific writing (Davarpanah 2007), and more useful articles are more frequently cited by researchers in a specific field (Abt 2000). Consequently, citation is a significant factor in scientific writing and production. Number of citations has been employed to measure the quality of scientific contributions, yet this method poses several limitations. First, it is sensitive to the dominant trends in different sciences. Citation behavior and the type of cited resources as two more major disparities in citometrics [citation-based metrics] in that they greatly vary in different scientific disciplines. Besides, numerous other structural and statistical factors such as the type of publication and their subjects, impact, scope of journals as well as the number of authors also influence citometrics. As all the benefits, uses and applications of scientific production are not conveyed merely through citations, therefore, citometrics as a criterion for evaluating the effectiveness of articles in expanding scientific knowledge has been criticized. Moreover, evaluating the amount of citation has several limitations and the increased rate of citation is not necessarily related to scientific merit (Davarpanah 2006). Hence, citing an article does not necessarily confirm its validity.

With the emergence and expansion of cyberspace and virtual social networks, scientific evaluations have also evolved and new metrics systems, namely altmetrics, have been introduced. These metrics improve our assessments of the impact of online journal articles (Mounce 2013). Altmetrics can provide classified information about an article's impact on the general public, different scholars and specialists. Moreover, they can monitor the use of various research products such as databases, software and blog posts (Priem, Piwowar and Hemminger 2012). Altmetrics measure different scientific exchanges including Tweeting, bookmarking and posting research results (Howard 2012). As altmetrics consider a very wide extent of scientific interactions and influences ranging from Facebook posts to Twitter reverberations, they can offer unprecedented methods for measuring the impact of authors and publications which can supplement traditional indicators (Bar-Ilan et al. 2012).

Khazragui and Hudson (2015) believe that altmetrics can prove to be most useful in supplementing citation count and journal impact factor, rather than in determining impact. However, certain aspects of impact including public engagement and its social implications may actually benefit from altmetrics. The extensive research conducted to assess the relationship between these two indices indicates a significant relationship between these two metrics.

Review of Literature

The literature on this topic can be broadly classified into two categories: first, those studies that concern the relationship between save and citation. Haustein and Siebenlist (2011) assessed 45 physics journals in the time span of 2004-2008. They found that the correlation between saving articles on CiteULike and their citations on the Web of Science is 0.21. Moreover, a strong positive relationship was found between the number of users and number of bookmarked articles and the total number of bookmarks. In another study by Bar-Ilan et al (2012) on citation, the publications of 57 speakers at the Leiden STI Conference in 2010 were investigated. The researchers found a significant correlation between Mendeley indicators and the number of citations on Scopus. Mazarei (2013) studied articles published in the fields of Information Science during 2004-2012 and found a weak positive and significant relationship between number of citations on the Web of Science and article bookmarks. A study of the publications of 100 Israeli and European astrophysicists revealed that there is a weak significant relationship between number of citations on Scopus and reading articles on Mendeley, yet this relationship was very strong at the level of authors (Bar-Ilan 2014). In a review article, Sugimito, Larivière and Haustein (2017) discuss that “Correlations between citations and Mendeley reader counts range from .2-.7, though the majority of analyses tend to report around .5 or .6. They argue that variations can be largely accounted for by disciplinary differences with particularly low correlations in the arts and humanities. Lower correlations can also be seen for samples with earlier publication dates as well as for very recent publications, due to the time needed for citations to accumulate”.

The second type of research assess the relation between traditional citometrics and altmetrics concern the relationship between discussion and citation. Eysenbach (2011) explored 55 articles indexed in the Journal of Medical Internet Research during 2009-2010 and concluded that there was a significant relationship between the number of Tweets and the number of citations. Moreover, the relationship between Google Scholar citations and number of Tweets was stronger that Scopus citations. Another study on the relationship between ArXiv publications, number of Tweets, Google Scholar citations and download counts in 4606 scientific articles yielded a significant correlation between these variables (Shuai, Pepe and Bollen, 2012). Thelwall et al (2013) studied 1.4 million articles indexed in PubMed and Web of Science during 2010-2012. They found a positive significant relationship between altmetrics and citometrics properties. In a meta-analysis, Bornmann (2014) examined the most frequently cited articles on the Web of Science. He also considered prominent altmetrics tools including Twitter, Mendeley, CiteULike, and Weblogs. He reported that the correlation between citation and the rate of micro-blogging (Twitter) was insignificant; the correlation between citation and number of weblogs was low, while it has a moderate to high correlation with the rate of bookmarks. Costas, Zahedi, and Wouters (2014) investigated 1,380,143 records on the Altmetrics website and found a weak positive and significant relationship between altmetrics and number of citations on the Web of Science. Therefore, Twitter and blog citations are two altmetric indicators mostly related to citation. Research has also investigated the relationship between altmetrics indices. For example, Huntington, Nicholas & Warren (2008), assessed the impact of digital visibility on online usage. The results demonstrated that usage did indeed increase as the result of improving visibility.

In terms of indirect relationship among altmetrics and citation index, Ebrahimy, Mehrad, Setareh and Hoseinchari (2016) have investigated the mediating role of save, discussion, and recommendation in the relationship between visibility and citation in biomedical articles. They employ path analysis method to determine the relationships between different variables in their descriptive correlational study. The study's model fit indices conveyed that visibility influences citation both directly and indirectly through the mediating role of save. Discussion had a significant, negative role in the relationship between visibility and citation, and recommendation did not have any significant mediating role in this relationship.

The review of literature conveys that most studies which concerned the direct relationship between altmetrics and citation in variety of social systems have indicated meaningful and positive correlation among them. However, the level of relationship has been variable in different research. It should be taken in to consideration that any of those studies has not been done according to a theoretical model. Regarding the indirect relationship between altmetrics and citation, just a research has been done although it has focused on the relationship between a few of altmetrics and citation in general and the efficacy of social systems and databases remains to be further explored. Therefore, the present study undertakes determine the direction of influence in various databases.

Objectives

This study aimed to assess the direction through which visibility metrics influence on citation in different social networks. Hence, a conceptual model has been proposed to test the interactions between these variables with mediating role of save and discussion in each case (Fig. 1). This was achieved by attempts to,

1. Determine the direction of the impact of visibility on citation index (in Scopus, Web of Science, PubMed Central, and CrossRef) via save (on CiteULike, Mendeley, and Figshare) in the PLOS system;
2. Determine the direction of the impact of visibility on citation index (in Scopus, Web of Science, PubMed Central, and CrossRef) via discussion (on Wikipedia, Facebook, and Twitter) in the PLOS system.

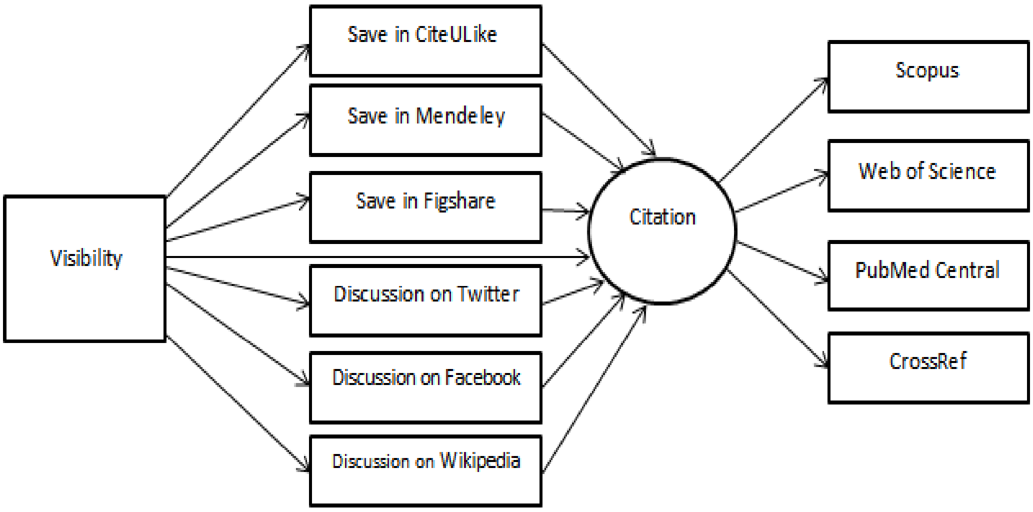

Figure 1. The conceptual model conveying the direction of the impact of altmetrics on citation in various indexes.

Based on the conceptual model above, visibility metrics might affect citation variable through save or discussion indices. To put it another way, visibility lead to save or discussion and as a result these two metrics affect citation. Furthermore, this process might be different in a wide spectrum of databases as well as social systems. The paths form these relationships have been assessed this in study.

Hypotheses

1. Visibility exerts an influence on citation index (in Scopus, Web of Science, PubMed Central, and CrossRef) via save (on CiteULike, Mendeley, and Figshare) in the PLOS system
2. Visibility exerts an influence on citation index (in Scopus, Web of Science, PubMed Central, and CrossRef) via discussion (on Wikipedia, Facebook, and Twitter) in the PLOS system.

Materials and Methods

This is a basic descriptive correlation study that aims to determine the direction of altmetrics' influence on citation through path analysis. Population included 90,728 research articles in all 7 biomedical journals indexed in the PLOS system during 2009-2013. Stratified and systematic random sampling method was employed and the sample size was calculated to be 1,892 articles by using Cochrane formula (table1).

Table1

Population and Sample Size based on systematic random sampling

Number	Name of Journal	Population Size	Sample Size
1	PLOS one	79,853	382
2	PLOS genetics	2,938	304
3	PLOS biology	849	208
4	PLOS pathogens	2,615	297
5	PLOS computational biology	2,100	281
6	PLOS medicine	473	146
7	PLOS neglected tropical diseases	1,900	274
Total		90,728	1892

The reason behind the selection of this time span was that each journal was indexed over a different period in the PLOS altmetrics system and 2009 proved to be their common initial point. Therefore, the starting point for our evaluation was set as 2009. On the other hand, a minimum time span is required to lapse for receiving citations. Although other factors like visibility, save, discussion and recommendation also require a time lag, theirs is considerably shorter compared to that of citation. Moreover, PLOS releases citation reports after a year of the of the articles' publication, and at the time of this study, 2014 citation reports were not yet released. Accordingly, 2009-2013 was determined to be the ideal period for this study. As theoretical backdrop of our proposed conceptual model was mainly concerned with PLOS and biomedical articles, this system of altmetrics was chosen. Besides, PLOS comprehensively presents the information related to research variables based on different social networks. Therefore, different interventional factors can be more closely observed, hence a more accurate model can be reached at.

Data collection included four stages: first, we referred to PLOS altmetrics system to delimit our scope to specific journals, research articles, and periods after 7 stages. Then, an adequate number of articles were selected from each journal using stratified random sampling. Second, the sample selected from each journal was individually analyzed, the values of all variables for each article were extracted via PLOS One system and manually recorded in a list, before being feed into SPSS. All these values were presented in integrated PLOS One system (that is save from CiteULike, Mendeley, and Figshare; discussion from Facebook, Twitter, and Wikipedia; recommendation from F1000; citation from Scopus, Web of Science, PubMed Central and CrossRef). In the end, necessary tests were applied and the proposed conceptual model was tested. Mean, standard deviation, and the correlation matrix were used to analyze the data in the first step. Then, path analysis was performed using AMOS software in order to assess the type of relationship between the variables.

Results

Table 2 shows the results of different descriptive variables. These variables did not have a normal distribution.

Table 2

Data regarding the descriptive variables of the study

Variables	Frequency	Mean	SD	Min	Max	Skewness	Kurtosis
Visibility	1866	6417.6	4821.42	594	48419	2.72	12.11
Save on CiteULike	1866	1.30	3.06	0	44	5.19	41.63
Save on Mendeley	1866	36.02	37.11	0	342	2.87	11.67
Save on Figshare	1866	26.05	24.87	0	321	3.85	26.04
Discussion on Twitter	1866	2.15	7.82	0	113	7.81	78.93
Discussion on Facebook	1866	6.22	20.74	0	270	6.6	55.33
Discussion on Wikipedia	1866	0.29	1.92	0	21	9.76	100.07
Citation on Scopus	1866	21.30	26.04	0	251	2.95	13.13
Citation on Web of Science	1866	20.22	24.54	0	226	2.9	12.77
Citation on PubMed Central	1866	12.56	16.08	0	182	3.16	16.1
Citation on CrossRef	1866	15.22	18.68	0	199	3.29	17.94

Besides descriptive variables analysis, the correlation between the variables was also calculated to validate further analysis. Table 3 illustrates the correlation matrix of the variables. There is a significant positive or negative relationship between the variables in several instances.

Table 3
Correlation matrix of the research variables

Variables	1	2	3	4	5	6	7	8	9	10
1. Visibility	1									
2. Save on CiteULike	0.36**	1								
3. Save on Mendeley	0.69**	0.52**	1							
4. Save on Figshare	0.01	-0.1**	- 0.13**	1						
5. Discussion on Twitter	0.21**	0.02	0.03	0.32**	1					
6. Discussion on Facebook	0.26**	0.03	0.11**	0.12**	0.41**	1				
7. Discussion on Wikipedia	0.21**	0.14**	0.19**	-0.05*	0.02	0.02	1			
8. Citation on Scopus	0.62**	0.28**	0.64**	-0.22**	-0.15**	0.02	0.20**	1		
9. Citation on Web of Science	0.64**	0.29**	0.66**	-0.22**	-0.17**	-0.003	0.21**	0.92**	1	
10. Citation on PubMed Central	0.61**	0.29**	0.64**	-0.22**	-0.19**	-0.03	0.20**	0..88**	0.93**	1
11. Citation on CrossRef	0.65**	0.29**	0.64**	-0.18**	-0.11**	0.03	0.21**	0..88**	0.92**	0.85**

* $P < 0.05$ ** $P < 0.001$

Since the variables of the model did not have a normal distribution and featured extreme skewness or kurtosis, the statistical technique of bootstrapping was used for analyzing the multiple variable relationships between different parameters.

In order to answer the research questions, the direction of the effect of altmetrics on citation in social networks was examined in the conceptual model (Fig. 1).

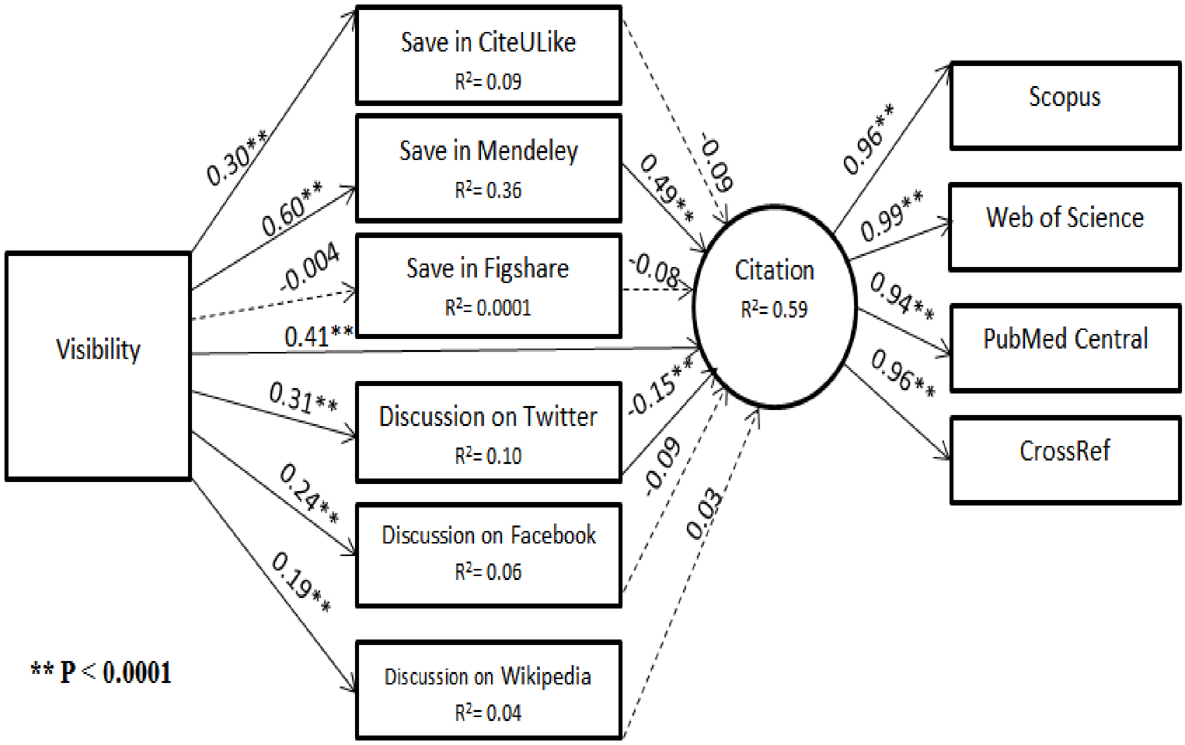

Figure 2. Results of path analysis regarding the effect of altmetrics on citation in social networks.

As shown in figure 1, the direct effect of visibility on most variables was confirmed. Moreover, only the effects of discussion on Twitter and save in Mendeley on citation were significant. Fitness indicators convey that the proposed model did not feature a suitable fit (table 4). In order to improve the fitness, the insignificant paths were omitted by referring to AMOS indices. The modifications were as follows: calculating the covariance between errors related to CrossRef and PubMed Central as well as calculating the covariance between the errors related to save on CiteULike and Mendeley, save on Mendeley and discussion on Facebook, and discussion on Facebook and discussion on Twitter (table 3). A good model fit was achieved after these modifications (table 4).

Table 4
Model fit indices for predicting citation through visibility and specific metrics

Indices	GFI	AGFI	IFI	CFI	RAMSEA
Preliminary model	0.89	0.82	0.93	0.92	0.12
Modified model	0.97	0.95	0.98	0.98	0.06

As illustrated in the results, the goodness of fit index (GFI) has greatly improved in the modified model. The adjusted goodness of fit index (AGFI) also increased from 0.82 to 0.95. The root mean square error of approximation (RMSEA) is also reduced from 0.12 to 0.06. The final fit model is shown in fig. 3.

As shown in fig. 3, this model predicted 57% of the variance in citation. Visibility positively and significantly predicts citation (β=0.40, P<0.0001). Moreover, visibility also predicts the amount of save in Mendeley (β=0.61, P<0.0001), discussion on Twitter (β=0.31, P<0.0001), save on CiteULike (β=0.30, P<0.0001), discussion on Facebook (β=0.24, P<0.0001), and discussion on Wikipedia (β=0.19, P<0.0001) significantly and positively. In other words, as the visibility of an article increases, the possibility of its saving on Mendeley and CiteULike, its discussion on Twitter, Facebook, and Wikipedia also increases. Is should be noted that visibility could not predict save in Figshare.

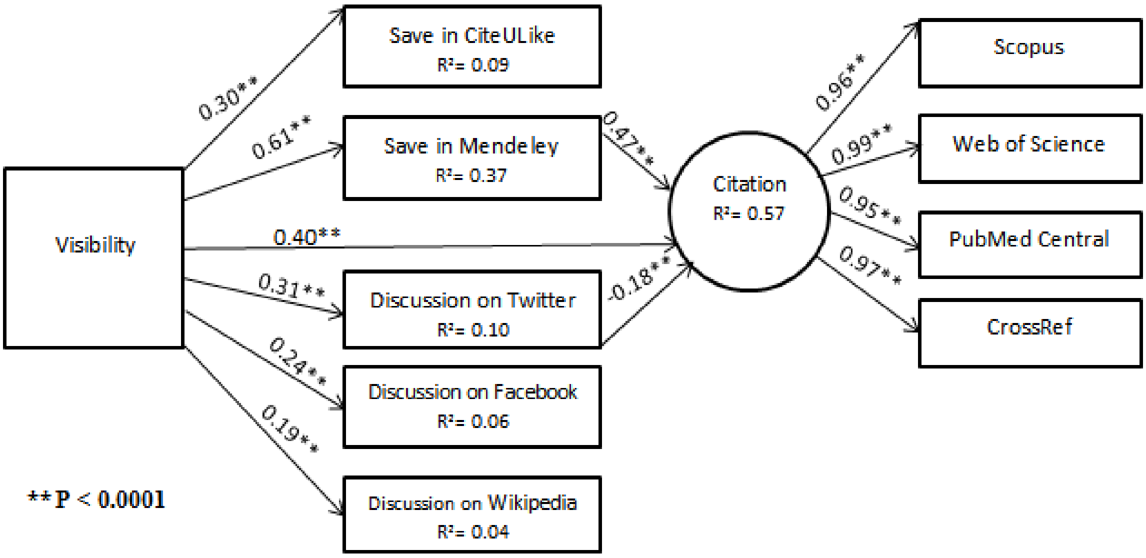

Figure 3. The final modified model of the effect of altmetrics on citation in social networks.

Considering the direct effects of intermediations on citation, it was found that only saving on Mendeley (β=0.47, P<0.0001) and discussion on Twitter could significantly predict citation. Save on Mendeley positively and significantly predicted citation (β=0.47, P<0.0001), while discussion on Twitter predicted citation negatively (β=-0.18, P<0.0001). In other words, the more articles are discussed on Twitter, the less they are likely to be cited.

Besides the direct relationships mentioned, the role of intermediating variables in the relationship between visibility and citation was also studied (table 5). The results conveyed that visibility not only directly influenced citation, but also exerted its effect through the intermediating variable of save on Mendeley and discussion on Twitter by 0.23 (P<0.0001). Accordingly, the total impact of visibility alongside with the intermediating effect of these two metrics was 0.63. Assessing the intermediating role of each of these two alternative metrics, we found that save on Mendeley served as the most important intermediation between visibility and citation (β=0.28, P<0.0001). In other words, visibility increased the number of saved articles in Mendeley, which in its turn, led to an increase in the number of citations.

The impact of visibility on citation increased to 0.68 by adding the intermediating variable of save on Mendeley. This is while discussion on Twitter negatively and significantly influenced the relationship between visibility and citation (β=-0.05, P<0.0001). In other words, visibility increases discussion on Twitter which in its turn decreases citation. In total, this intermediation reduced the total effect of visibility on citation to 0.35.

Table 5
The indirect and total effect of visibility on citation through the intermediating role of several altmetrics

Intermediating variables	Indirect effect		Total effect	
	β	P	β	P
Save in Mendeley	0.28	0.0001	0.68	0.0001
Discussion on Twitter	-0.05	0.001	0.35	0.001
All intermediations	0.23	0.0001	0.63	0.001

Discussion

The results of this study conveyed that the effect of visibility on citation increased up to 0.68 by adding the variable of save on Mendeley as an intermediating factor. This is while citation did not alter after adding this variable on CiteULike and Figshare. Therefore, in answer to the first research question it should be stated that the only Mendeley can increase the impact of visibility of citation. Besides, save could significantly predict citation only on Mendeley (β=0.47, P<0.0001). Also, the results showed that visibility had a positive and significant relationship with save on Mendeley and CiteULike.

Our results are consistent with those of Li and Thelwall (2012). They believe that the number of Mendeley users is larger than that those of CiteULike, and Mendeley attracts still more users. These factors increase the rate of saving articles which, in its turn, would improve the rate of citation. Bar-Ilan (2012) argues that Mendeley has a more comprehensive subject coverage which persuades more users to upload their works on Mendeley. They also tend to search its subject directory, hence its articles are more frequently cited. Mazarei (2013) attributed this to factors including the large number of bookmarked documents on Mendeley, and its larger number of users. Bar-Ilan et al (2012) contend that as Mendeley represents recent findings and since elder articles are less frequently bookmarked, the articles on Mendeley are more frequently cited. Mohammadi and Thelwall (2013) also note that recent findings are more pertinent to citing scholarly resources. Although the valuable of elder research is not denied, researchers do not tend to cite it as frequently as recent studies.

Furthermore, Mendeley is one of the most prevalent altmetric tools. CiteULike does not provide any login information for its users, while Mendeley even records such demographic data as country of origin, and the occupational status of its users (Fenner 2014). This is yet another reason why Mendeley attracts more users.

Other researchers explain the fact that CiteULike cannot predict citation by maintainin that tagging systems such as CiteULike help researchers organize and tag electronic resources. They also provide the opportunity to share these resources with other users (Good, Tennis and Wilkinson 2009). But incorrect tagging leads to misunderstanding the content and this will reduce citation. Moreover, the problems in tagging by using uncontrolled key words have weakened these systems. A single tag might be used in several disparate occasions due to its ambiguity. A similar problem arises because of a deficiency in employing synonymous terms (Mathes, 2004). Public rating structures feature non-monitored use of overlapping terms, antonyms, and unconventional words which affect their validity as instruments for measuring the impact of knowledge (Nowroozi, Mansouri and Hosseini 2007). These factors influence save, hence citation, on CiteULike.

It was also revealed that Figshare does not have a significant role in changing the rate of saving and citations of publications so it is not included in the model. This is because Figshare is a much less popular network. In other words, scholars have not acknowledged it yet. Another reason could be that this network is neither affiliated with nor in close collaboration with any publishing house; as a result, its possibilities are not fully revealed yet.

Thus, visibility can predict save on Mendeley and CiteULike, but only Mendeley can predict citation. Therefore, as an intermediation between visibility and citation, save can predict citation only on Mendeley.

It was also found that discussion as an intermediation on Twitter relates visibility and citation negatively and significantly ($\beta = -0.05$, $P < 0.001$). In other words, visibility boosts the discussions of an articles on Twitter and this will reduce the rate of its citation. Discussion as an intermediation on Twitter reduces the total effect of visibility on citation from 0.63 to 0.35. This is while discussion on Facebook and Wikipedia could not predict alternations in citation. Therefore, regarding the second research question, it can be concluded that discussion has a negative and significant role as an intermediation in the relationship between visibility and citation only on Twitter.

Besides, discussion significantly and negatively predicted citation on Twitter ($\beta=-0.18$, $P<0.0001$). That is to say the more articles are discussed on Twitter, the less they are cited. This is inconsistent with the results of Eysenbach’s study (2011). Eysenbach (2011) avers that 75% of the articles with high Tweet rates also featured high citation rates and that this does not hold true for only 7% of all articles. He also concludes that Tweets are able to predict citation in the first three days after an article appears. Accordingly, time plays a vital role in citation. Eysenbach adds that this is even more apparent in the case of Google Scholar citations mainly because Google Scholar includes a wide range of resources including non-academic journals. Another shortcoming of a metrics system based on Twitter is that Twitter primarily measures popularity which is more relevant to entertainment industry rather than academic situations. So the results of such metrics can even be hazardous in case they are not supplemented with other indices, especially in medical and scientific fields.

We also found that visibility positively and significantly predicted discussion on Twitter ($\beta=0.31$, $P<0.0001$), Facebook ($\beta=0.24$, $P<0.0001$), and Wikipedia ($\beta=0.19$, $P<0.0001$). That is to say, the higher the visibility of an article, the more likely it is to be discussed on these social networks. This could be attributed to the fact that users interact with each other, exchange ideas, and ask for support and guidance through discussing articles on Twitter (Grosseck and Holotescu 2008). Similarly, Facebook is one of the most important social networks assisting researchers in their scientific careers by creating a forum for their interactions, although it is mainly intended for recreation and social interaction (Madge et al. 2009). Facebook facilitates the representation of self and interpersonal messaging. And people can also join groups that follow their personal or academic interests (Ellison, Steinfield and Lampe 2007). Wikis are also Web2 elements used for enriching the learning process (Parker and Chao 2007) and users refer to and discuss its documents on various social networks.

We also found that discussion on Twitter, Facebook, and Wikipedia did not increase citation. One explanation could be that these three networks are public with a broadly general interest and no monitoring on content; therefore, most of materials discussed or posted on them are not deemed scientifically valid. Researchers, as the result, do not tend to trust their content which also dissuades scholars from citing them. It can be concluded that visibility can predict discussion on these three social networks, but discussion as an intermediation can significantly and negatively predict citation only on Twitter.

Conclusion

Identifying the most effective social networks and paths leading to citation helps science policy makers, journal editors and scholars determine the most influential methods of online scientific interaction. Due to their promises, these social networks might be employed for scientific evaluations in future. Owing to focusing this study on PLOS which is in medicine field, it is recommended that other subject areas would be investigated. Illustrating the effective paths and social systems in a wide range of categories would provide a beneficial distinction for a more precise evaluation. Besides, the medicine scholars are recommended to save their publications in mendeley in order to raise their impacts. Journal editors should employ this media to cultivate journal ranking indices as well.

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