

**If I tweet will you cite? The effect of social media exposure of articles on downloads and citations**

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**Abstract**

**Objectives:** We sought to investigate whether exposing scientific papers to Social Media (SM) has an effect on article downloads and citations. **Methods:** We randomised all International Journal of Public Health (IJPH) original articles published between December 2012 and December 2014 to SM exposure (blog post, Twitter and Facebook) or no exposure at 3 different time points after first online publication. **Results:** 130 papers (SM exposure=65, control=65) were randomised. The number of downloads did not differ significantly between groups ( $p = 0.60$ ) nor did the number of citations ( $p=0.88$ ). Adjusting for length of observation and paper's geographical origin did not change these results. There was no difference in the number of downloads and citations between the SM exposure and control group when we stratified for open access status. The number of downloads and number of citations were significantly correlated in both groups. **Conclusions:** SM exposure did not have a significant effect on traditional impact metrics such as downloads and citations. However, other metrics may measure the added value that social media might offer to a scientific journal, such as wider dissemination.

**Keywords:** social media, citations, downloads, bibliometrics, Twitter, Facebook

**Introduction**

The use of social media (SM) continues to increase among the wider public (Smith 2014) and academics alike (Bik and Goldstein 2013). Scientific journals have started using SM to disseminate their content, although only 28% of medical journals have been found to have a Twitter account (Cosco 2015). The *International Journal of Public Health* (IJPH), owned by the Swiss School of Public Health (SSPH+)(Künzli et al. 2015), has hosted a blog since 2011 and created Facebook and Twitter accounts in 2012 (Tonia 2014). Investing in SM entails additional costs for the user, so the question is whether SM adds enough value to make it worth it for a scientific journal to engage with SM audiences. Added value might include expanding academic interest in research published by IJPH, stirring up debate over IJPH articles, and increasing the number of citations received by IJPH articles.

Article accesses and downloads are both positively correlated with citations (Brody and Harnad 2005;Liu et al. 2013;Perneger 2004). Some studies have examined the correlation between SM exposure and subsequent article downloads and citations for specific SM like Twitter (Eysenbach 2011;Shuai et al. 2012;Terras 2012;Haustein et al. 2014), Facebook (Ringelhan et al. 2015), Wikipedia (Evans and Krauthammer 2011), online reference manager software (Li et al. 2012), or multiple types of SM (Sorenson 2014;Thelwall et al. 2013) and subsequent article downloads and citations. These studies reported different degrees of positive association between exposure to SM and article downloads and citations. Such correlational studies, however, cannot distinguish whether SM exposure increases the impact of papers, or whether more interesting and significant articles get more SM attention when they are published (Fox et al. 2014).Instead, randomized controlled studies can identify causal relationship between SM exposure and downloads or citations.

We found only one randomised controlled trial (Fox et al. 2014) that assessed the influence of SM exposure on subsequent article views (which includes downloads). This study was conducted with articles from a high-impact journal (IF at the time of study: 15.2). It found no influence of SM exposure on article views. We found no randomised controlled trial that assessed the effect of SM exposure on citation of published papers. There are already calls for more firm research in this area (Moorhead et al. 2013), and we intended to address this need.

We explored the association between SM exposure, and downloads and citations of original articles published in IJPH, a medium-impact journal (IF at the time of study: 1.97-2.70). We hypothesized that SM exposure to original papers would increase the number of times those papers were downloaded as PDFs and subsequently cited.

## **Methods**

### **Design**

We used an experimental study design. We included all original articles published online between December 2012 and December 2014, regardless of subject, and excluded reviews, brief reports, editorials and commentaries. Since each IJPH paper already had a random publisher-assigned DOI number, we used the second to last digit of the DOI number to randomise all original articles to either the SM exposure group or the control group (odd number: experimental group; even number: control group).

### **SM exposure**

The SM exposure was tested on each article in the SM exposure group, in three different venues, and applied at three different time points for each article. Articles in the control group received no SM exposure. When papers in the experimental group were published online, they received exposure in the IJPH blog, Twitter and Facebook accounts: a short post presented the paper in the blog and a Tweeter and Facebook update summarized the main message of the paper and provided a link to it. Two weeks after the first intervention, the Tweet was repeated (second intervention). Ten weeks after the second intervention, IJPH posted about the article on Facebook and Tweeted again. One of the authors (TT) posted all the notifications, between Monday and Friday. All three interventions were made on the same day of the week, and time of day, for each paper. To ensure consistency, we set up automatic posting on Facebook so the third exposure was published at the predefined day and time. We used Tweetdeck (<https://tweetdeck.twitter.com/>) to automatically post Tweets for the second and third exposure. TT performed random checks to ensure that the automated updates were published as planned. Posts were written in plain language and highlighted the main point of the paper. Whenever possible, paper authors were “tagged” if they had Twitter accounts, so they were informed about the exposure.

### Endpoints

There were two primary endpoints: (1) the number of full-text article downloads; and, (2) the number of article citations from online publications up to March 31<sup>st</sup>, 2015. IJPH’s publisher, Springer, provided download data that included the number of downloads per paper, and per day, after the paper was published online. We used ISI Web of Science to identify articles citing the papers included in the study

[[http://apps.webofknowledge.com/UA\\_GeneralSearch\\_input.do?product=UA&search\\_mode=GeneralSearch&SID=R2v9wly4rWptVrWi6kU&preferencesSaved=](http://apps.webofknowledge.com/UA_GeneralSearch_input.do?product=UA&search_mode=GeneralSearch&SID=R2v9wly4rWptVrWi6kU&preferencesSaved=)]. We defined the online publication date of the citing article as the date of citation. We considered citations until March 31<sup>st</sup> 2015. We also evaluated the possible effect of open-access status on both downloads and citations. In IJPH, some papers are open access once they are published online. Other papers, like “The Editors’ Choice”, gain open access status once they appear in the print issue. For the purposes of this paper, we grouped both early and late open access papers to the “open access” category.

### Statistical analysis

We used the Wilcoxon rank sum test to determine differences in quantitative variables between the two groups. Correlations between quantitative variables were assessed using Spearman’s rank correlation coefficient; for these analyses we aggregated download and citation data into 4 week intervals.

Because length of observation time affects citation and download counts, we conducted negative binomial regression analyses, modelling the influence of observation time as a cubic polynomial of the natural logarithm of observation time in the linear predictor. Despite randomisation, there was a significant association between region and intervention (Chi<sup>2</sup>-test = 0.016), so we repeated the analysis after adding the region of corresponding author as an additional factor. We also ran models with separate intervention effects for the three main regions where the papers originated.

We stratified group comparisons of citation and download counts by open access status. Among the exposed group, we also determined if the day of the week the article was exposed affected the two main outcomes. We examined the evolution of downloads and citations per group over time. All statistical analyses were conducted using STATA 14.0.

## Results

### Study sample characteristics

We randomised 133 papers between December 2012 and December 2014 (68 in the SM exposure group; 65 in the non-exposure group). We excluded three papers in the exposure group because we made mistakes in the application of the intervention protocol ( $n = 2$ ) or there was already a citation before print publication in IJPH ( $n=1$ ). We present the characteristics of the articles we included (Table 1). There were only 9 open access papers (3 in the SM group; 6 controls). Almost half of the papers were randomised on Tuesdays, fewest papers were randomised on Fridays. In the exposure group, the mean number of days between online publication and first exposure was 9.3 (SD: 7.62, range 0-26). In the experimental group, more corresponding authors came from Europe (71%) than in the control group (46%), but more authors came from North America, Australia and New Zealand in the control group (29%) than in the experimental group (14%); more authors in the control group also came from Africa, Asia and South America (25%) than in the experimental group (15%). Follow-up time (time of randomisation until time of data collection) ranged from 90 to 821 days (mean 407.67 days, SD 227.18) for all papers.

### Effects of SM exposure on downloads

There were 25,641 downloads: 12,466 in the SM exposure group, and 13,175 in the control group. The mean number of downloads per paper was 191.8 (SD: 156.1, median: 133.00, range: 54-910) for the SM exposure group and 202.7 (SD: 181.1, median: 147.00, range: 53-1035) for the control group. The number of downloads did not differ significantly between groups (Wilcoxon rank sum test,  $p = 0.60$ ). Figure 1a shows the evolution of number of downloads over time, in 4-week intervals for the two groups. We observed a very similar pattern between groups, peaking at the beginning, steeply decreasing within the first 4 weeks after online publication and slightly decreasing later until the end of the study.

Table 2 shows that, negative binomial regression analysis brought the rate ratio (RR) of SM exposure vs. control downloads almost to 1 (RR 1.03, 95% CI 0.88 to 1.21;  $p=0.71$ ; incidence rate difference:  $0.02 / \text{day}^{-1}$ ). Adjusting for the corresponding author's region of origin did not markedly alter the rate ratio (RR 1.06, 95% CI 0.90 to 1.25;  $p=0.48$ ). When we ran the model with separate exposure effect variables for the three main regions it returned very similar estimates and did not improve on the previous model ( $p=0.99$ ).

### Effects of SM exposure on citations

During the follow-up period for the 130 manuscripts, there were a total of 105 citations; 55 in the SM exposure group, and 50 in the control group. The mean number of citations per paper was 0.85 (SD 1.54, median: 0.00, range: 0-8) for the SM exposure group, and 0.77 (SD 1.26, median: 0.00, range: 0-6) for the control group. This difference in the number of citations was not statistically significant between the two groups (Wilcoxon rank sum test  $p = 0.88$ ). Figure 1b shows the time evolution of number of citations in four-week intervals for the two groups. The intervention group seems to peak at about a year, but the total number of citations is too small to hypothesise about this difference.

Negative binomial analysis (Table 2) provided a 1.25 rate ratio of citations between exposure and control (RR 95% CI 0.77 to 2.04;  $p=0.37$ ; incidence rate difference:  $0.00038 / \text{day}^{-1}$ ). Further adjusting for region of origin slightly decreased the effect (RR 1.20, 95% CI 0.72 to 2.00;  $p=0.48$ ). Running the model with separate intervention effect variables for the three main regions for corresponding author slightly increased the effect for Europe (RR 1.49) but reduced it to less than 1 for North America, Australia and New Zealand, and for Africa, Asia and South America. None of these differences were statistically significant ( $p=0.43$ ).

#### Influence of open access status

When we considered all papers from both groups together, we found significantly more downloads for the 9 open access articles (mean download per article: 556.9, median: 627.00, SD: 335.2, total number of downloads 5012) than for the 121 non-open access articles (mean: 170.5, median: 137.00, SD: 112.2, total number of downloads: 20,629;) (Wilcoxon rank  $p<0.001$ ). The number of citations for open access papers (mean: 0.56, median: 0.00, SD: 0.73, total number of citations 5;) did not differ significantly from those of non-open access papers (mean: 0.83, median: 0.00, SD: 1.44, total number of citations: 100;) (Wilcoxon rank sum test  $p=0.98$ ). When we stratified by open access status, we found no effect of the SM exposure on downloads and citations (Online Supplement).

#### Correlations

Later publication date shortened the length of time between publication and the end of our study. As expected, this was associated with fewer downloads and citations. The number of downloads and the number of citations significantly correlated for all papers (Spearman's  $\rho = 0.529$ ,  $p<0.001$ ), both in the SM exposure group and the control group. Correlation was stronger in the SM exposure group ( $\rho=0.67$ ,  $p<0.001$ ) than in the non-exposure group ( $\rho 0.37$ ,  $p=0.003$ ; Figure 2). A permutation test revealed the significant difference between the two correlation coefficients of the two groups ( $p=0.01$ )

## Discussion

#### Summary of results

Exposure to SM did not significantly increase the number of downloads and number of citations for IJPH papers. This result did not change when we adjusted for length of observation and the paper's geographical origin. We saw no significant differences between SM exposure and control groups in number of downloads or citations when we stratified results for open-access status, though this lack of difference might result from the low number of open-access status. The number of downloads and number of citations were significantly correlated in both groups, but the correlation was stronger in the SM exposure group. SM exposure and article downloads

Unlike our study, most observational studies showed some degree of positive correlation between SM exposure and subsequent article hits or downloads (Sorenson 2014;Allen et al. 2013;Shuai et al.

2012). The difference between the results of these studies and our results may be due to the difference in study designs (observational versus randomised). Observational studies can show association between SM exposure and article downloads, but they cannot prove exposure leads to more downloads (Fox et al. 2014).

Randomised trials could help shed more light on the direction of the relationship between SM exposure and downloads. Our results agree with Fox et al. (Fox et al. 2014), who randomised 243 papers published in *Circulation* to either exposure to SM via the journal's Twitter and Facebook feeds, or no exposure. This study found no difference in the median 30-day page views between exposed or non-exposed papers.

### SM exposure and article citations

Some observational studies that looked at the effect of SM exposure (mainly Twitter) on subsequent article citations found significant correlations (Shuai et al. 2012;Eysenbach 2011;Haustein et al. 2014;Thelwall et al. 2013).

The difference between ours and observational studies may be explained by the randomised design we chose. Like article downloads, mentions of scientific paper in SM may be early indicators of a paper's impact (Fox et al. 2014). Better articles, on more interesting topics, might receive more mentions. Citation decisions of authors probably depended more than on SM exposure on the paper topic and scientific quality, and the relevance or generalisability of its content. It is also possible that the SM audience might not be the same audience that would cite the papers. Haustein et al. (Haustein et al. 2014) suggested that low SM uptake by scientists might explain the difference between Twitter citations and more "traditional" measures of article impact. Top tweeted articles in the Haustein study were the ones that had more humorous or curious content, and it is possible Tweets were made more often by the general public than by scientists. SM metrics indicate a different kind of impact than downloads and citations (Haustein et al. 2014) and may be complementary (Liu et al. 2013). Impact may also not be a simple function of SM reach (Allen et al. 2013).

### Results of open access status and downloads and citations

It was not our primary aim to investigate the influence of open access status on the effects of SM exposure, but we looked into possible differences deriving from a small number of open access articles that were included in our experiment. Our results agree with those of Davis' randomised study (Davis et al. 2008) who found that open access papers were downloaded more often, but not cited more in the first year after publication. When we stratified the analyses of effects of SM exposure for open-access status, results showed no significant differences between SM exposure and non-exposure groups for either downloads or citations. Our study agreed with the results of previous studies (Brody and Harnad 2005;Liu et al. 2013;Perneger 2004): the number of downloads and number of citations were significantly correlated in both groups, but the correlation was stronger in the SM exposure group.

## Strengths and limitations

To our knowledge, this is the first randomised controlled trial assessing the effect of SM exposure on citations of published papers. We included only the same type of articles (original articles), kept a strict and consistent schedule and mode of exposure. SM exposure was comprehensive, and used three different platforms (blog, Twitter, and Facebook).

This study has some limitations. We were surprised to find that the geographical origin of the corresponding authors of the papers differed significantly between the two randomly assigned groups. We consider this difference a chance finding, and when we adjusted for this co-variate, our findings remained the same.

The statistical power to observe a statistical significance on citations was limited by the number of published articles within the experimental period of 24 months and a relatively short observation period for some papers (range of observation 3-27 months). The observed effect was small and in order for it to have reached statistical significance the sample size would have to be 8 times bigger given the 24 months experimental period, something that would not be possible for IJPH, since we already included all the published original articles. And even if the effect had reached statistical significance in a larger study it would probably not have been relevant. Moreover, citations accrue over time: IJPH has a higher five-year than two-year Impact Factor and a cited half-life of 3.9 in 2015 (that means that articles published in 2012-2015 account for 50% of all the citations to the Journal in 2015). IJPH articles were cited, on average, 1.8 times as often in the second year after they are published than in the first year (Thomson Reuter's Journal Citation Reports 2009-2014.) To fully capture the difference SM media exposure makes for citations, therefore, it may be worth expanding the observation period.

Although we randomised the articles to a self-performed highly standardised SM intervention, we could not influence or assess SM exposure from other sources, like the authors. For instance, Sorenson (Sorenson 2014) found that among papers exposed to SM by the journal, the only one also promoted on SM by the paper's author had the highest number of access. We could not assess the effect of the number of article views, which was reported as the best measure (Yan and Gerstein 2011). We could only access the number of downloads, since this is the data the publisher collects. View or download statistics are, at best, a "crude measure of actual use" which may not be enough to indicate the influence of an article (Li et al. 2012). The randomised design might also have limited the opportunities to create exposure for some papers that might be of more interest to the general public.

The IJPH SM profiles do not have large numbers of followers and its Impact Factor is of medium size, which also could have affected the final result. Right before we started this study, we had 140 Facebook "likes" and 403 Twitter followers. Before we finished randomising, our Facebook like had increased to 399 and our Twitter followers to 1,845. Thus, results might not be generalizable to journals that have a much higher number of followers or a higher Impact Factor (Allen et al. 2013). But the only other randomised controlled study that measured the effect of SM exposure on article downloads (Fox et al. 2014) was done on a journal that had larger audiences on Facebook (28,000) and Twitter (4,800). Similarly, the journal used for this study had a higher Impact Factor (15.2 at time of study) compared to IJPH (between 1.97 and 2.70 at the time of study). This study also found SM exposure had no effect on downloads, suggesting no influence of size of the SM audience or the

Impact Factor. Finally, only few IJPH papers had open-access status and thus our results might not be generalizable to journals that are available open access. Results on article views from the *Circulation* trial (Fox et al. 2014) were, however, similar to ours even if the papers included at this study were available open access.

#### Implication for further research

Given the few randomised controlled studies thus far, the effect of exposing papers on SM should continue to be monitored. Future studies should also take into the scope of the journal (broad versus narrow) and the subject of the articles, because results may differ between disciplines (Haustein et al. 2014; Ringelhan et al. 2015).

Scientific articles do not yet get much exposure on SM (Thelwall et al. 2013; Sorenson 2014): A recent study assessing data for 1.3 million papers found that 21.5% of them received at least one Tweet; 4.7% were shared on Facebook; and 1.9% were mentioned in a blog (Haustein et al. 2015). Changes in the frequency and type of SM exposure may affect article download and citation rates. Researchers should also account for time trends in the relationship between SM exposure, downloads, and citations (Yan and Gerstein 2011; Thelwall et al. 2013). The role SM plays in the research process should also be studied. Papers exposed on SM might exert more influence on hypothesis generation or choosing research topics. If this is the case, the effect of SM might be bigger on downloads but not on citations, as researchers might use other channels and motivations when compiling their reference lists of their paper. Indeed, citing behaviour has been found to be complex, involving not only the trustworthiness and credibility of the source but also the use of social and research contacts (Thornley et al. 2015). We also need to know more about the association between more complete SM impact metrics such as Altmetric score, and other impact metrics like citations: previous research has shown that Altmetric and citation metrics are related but Altmetrics might capture other types of impact as well (Costas et al. 2014). Better understanding of this type of impact might help us identify the best way to quantify the dissemination of information from scientific journals using SM (Fox et al. 2014).

#### Conclusion

At least within the first 3-27 months of observation, SM exposure did not change the number of downloads and citations in papers published in the International Journal of Public Health. We may update the data on downloads and citations and analyse it 3-4 years after the end of this intervention to have a more complete picture on the effect of SM exposure for our journal.

For the owner of an academic journal, the question remains how to determine whether investment in SM “adds value”. Though downloads and citations have become a common quality measure of scholarly journals, other criteria may measure added value from SM activity for journals. Using SM can help journals to control how their content is being presented and disseminated, avoiding miscommunication. Furthermore, SM may help disseminate scientific papers to mainstream media and reach a wider public that would never write and publish research papers (but could – nevertheless- benefit from reading them).

To further evaluate such added value, metrics other than article downloads and citations need to be monitored in parallel. Altmetric scores or citations in Google Scholar, for instance, include a wider range of sources than traditional impact metrics and can offer additional information on the effect of SM on scientific papers and journals. Finally, a scientific journal can use SM in other ways apart from simply posting tweets or status updates on SM: twitter chats and twitter journal clubs are two examples of more elaborated use of SM (Colman and Anand 2015;Mehta and Flickinger 2014;Goff et al. 2015) and present future challenges for use and evaluation.

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Funding: This study received no funding

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors

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**Table 1:** Characteristics of the articles included in the Randomised Control Trial, by exposure status (Social Media (SM) exposure, no SM exposure (Control). International Journal of Public Health, for articles published between December 2012-December 2014

Characteristic	SM exposure (n=65)	Control (n=65)	Difference between groups (Chi2-test)
<b>Open access (total)</b>	3	6	p=0.30
<b>Open access since first online publication*</b>	1	2	
<b>Origin of corresponding author</b>			p=0.02
<b>Europe</b>	46 (70.77%)	30 (46.15%)	
<b>North America, Australia and New Zealand</b>	9 (13.85%)	19 (29.23%)	
<b>Africa, Asia and South America</b>	10 (15.38%)	16 (24.62%)	
<b>Day of first exposure**</b>			
Monday	14 (21.54%)	N/A	
Tuesday	31 (47.69%)	N/A	
Wednesday	5 (7.69%)	N/A	
Thursday	12 (18.46%)	N/A	
Friday	3 (4.62%)	N/A	
<b>Mean; median range of time of follow-up (days)</b>	388; 324; 90-783	427; 426; 90-821	p=0.38 (Wilcoxon rank sum test)

\* In International Journal of Public Health, some papers are open access since their online first publication; some papers, however, get open access status when the printed issue is published, if –for instance- are chosen by the Editors.

\*\* Second and third exposures were always performed on the same day and time as the first exposure

**Table 2:** Estimated incidence rate ratios (RR) of citations and downloads associated with social media exposure. International Journal of Public Health; for articles published between December 2012 and December 2014; downloads and citations for these articles between December 2012-March 2015

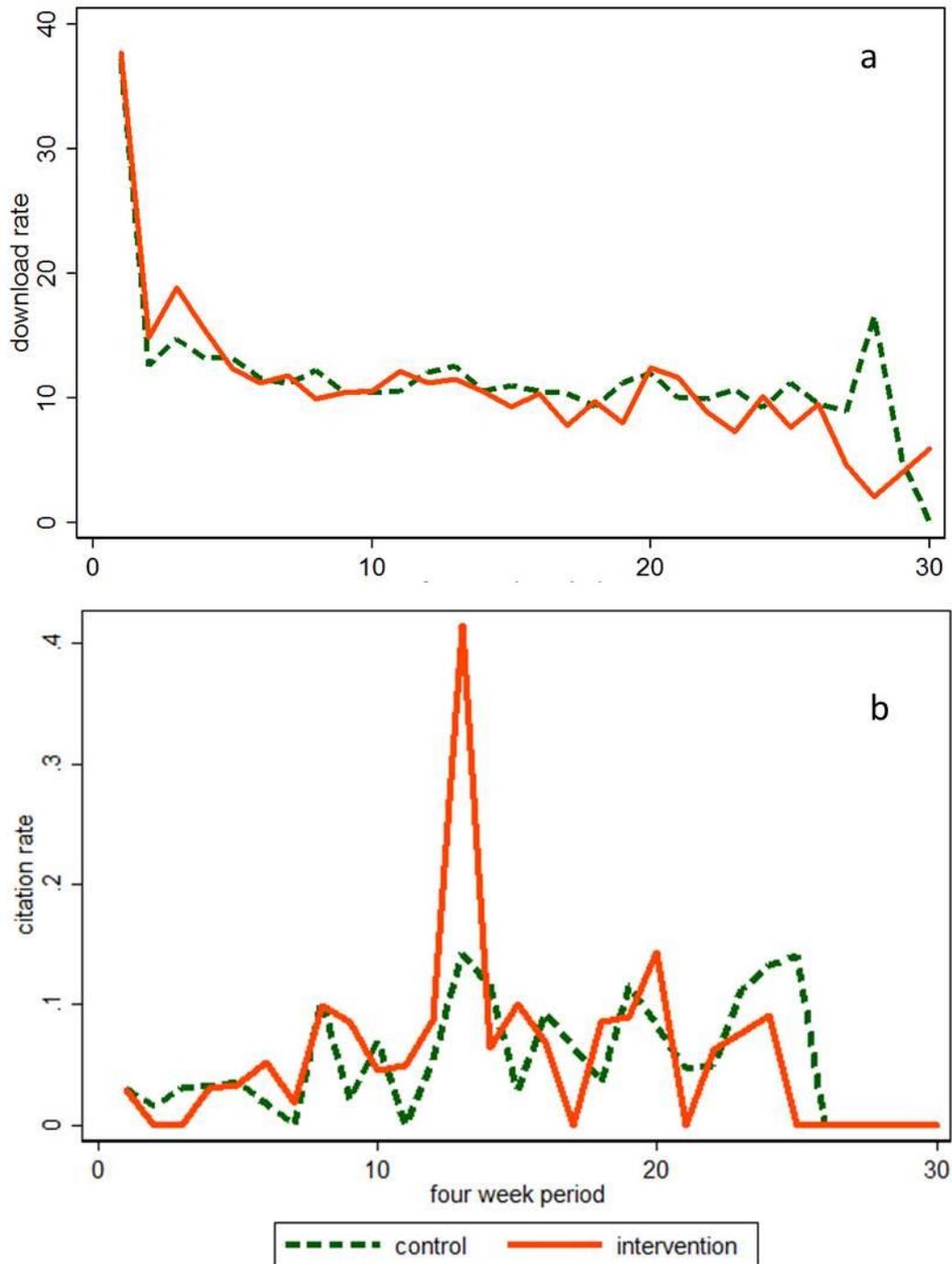
	RR	95%-CI	p-value
number of downloads			

unadjusted	1.03	0.88	1.21	0.71
after adjustment for region <sup>1</sup>	1.06	0.90	1.25	0.48
region 1	1.06	0.86	1.30	0.99*
region 2	1.05	0.73	1.50	
region 3	1.08	0.76	1.55	
without open access	1.10	0.96	1.26	0.16
<b>number of citations</b>				
unadjusted	1.25	0.77	2.04	0.37
after adjustment for region <sup>2</sup>	1.20	0.72	2.00	0.48
region 1	1.49	0.81	2.73	0.43*
region 2	0.68	0.21	2.26	
region 3	0.73	0.12	4.31	
without open access	1.25	0.76	2.04	0.38

<sup>1</sup> region 1 = Europe, region 2 = North America, Australia, New Zealand, region 3 = Africa, Asia, South America

\* p-value of interaction between region and social media coverage

**Fig. 1:** Download rate (a) and citation rate (b) by time (4 week periods) since publication. International Journal of Public Health for articles published between December 2012 and December 2014); downloads and citations for these articles between December 2012-March 2015



**Fig.2:** Relationship between numbers of downloads and number of citations in the SM exposure group (Spearman's rho 0.668;  $p < 0.001$ ) and the control group (Spearman's rho 0.365;  $p = 0.003$ ). (for both groups: Spearman's rho 0.529;  $p < 0.001$ ). International Journal of Public Health, for articles

published between December 2012 and December 2014; downloads and citations for these articles between December 2012-March 2015

