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Original Article

Twitter Research Synthesis for Health Promotion: A Bibliometric Analysis

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Abstract

Background: This study enriched our understanding by systematically reviewing knowledge management twitter health (KMTH) articles extracted from Web of Science (WoS) using cartography analysis through VOSviewer– for the last 11 years.

Methods: A total of 798 KMTH articles were found from 2009 to 2019, analyzed based on the most co-occurrence keywords of KMTH articles.

Results: Three clusters emerged through cartography analysis; Cluster 1: Twitter as health education and health promotion platform; Cluster 2: Twitter as public health promotion platform and Cluster 3: Twitter as health sentiment platform through big data and machine learning.

Conclusion: This study opened new avenues for all health care providers to utilize Twitter as a KM platform to promote health care. This is the first bibliometric analysis of KMTH publications according to our best knowledge.

Keywords: Twitter; Bibliometric analysis; Health promotion; Knowledge management

Introduction

Twitter has been used in different health contexts at both individual and organizational levels platform where people can quickly and easily contribute and engage in new forms of knowledge seeking, knowledge acquisition and knowledge dissemination behavior (1,2). They also supported traditional models of engagement such as communities of practice – CoP (3,4) . For instance, health-minded individuals discuss health problems with their peers and seek support from experts (5). The participative nature of Web 2.0 levels off the playing field for knowledge sharing in CoPs. Individuals with varying degrees of expertise from medical experts to lay-persons can seek and disseminate health information (6). For example, twitter-based community *Health Care Social Media Canada* (#hcsmca), founded in 2010, used twitter platform for health related knowledge sharing and health promotion.

The concept of CoP has put forward the concept of e-health (7) and m-health (8) based on web 2.0. E-health and m-health not only the emblem of today's medicine but also providing a platform to seek and disseminate health related knowledge (9). TrialX is a twitter based service that helps patients to find clinical trials. TrialX creates a match among the patient's health profile, lab results, and medications, as well as locations (10). Later on, the seminal initial publications: Hawn (7) and Vance et al (11) acted as catalyst to reengineer today's health information and promotion. One fact is undeniable that researchers have become increasingly interested in this research area in recent years. For example twitter role in women health (12), twitter role for weight loss support (13), Vaccine awareness on twitter (14) and twitter in travel medicine (15). Twitter provides public health researchers with a unique big data source due to the content's real-time existence, and the ease of accessing and searching publicly accessible information. Prior studies have exhibited huge contribution of twitter as a knowledge acquisition (16), knowledge seeking (17) and knowledge dissemination (18) platform and also its undeniable role in health promotion as eHealth and m-health.

Prior bibliometric studies of Social Media (SM) have been conducted with respect to different research areas e.g. event detection in SM (19), bibliometric of sentiment analysis (20) and bibliometric of SM in knowledge management (21). Whereas some studies conducted bibliometric analysis of different health problems using SM as platform e.g. Muller et al (22) provided an overview of the eHealth and mHealth research field related to physical activity, sedentary behavior, and diet. Li et al (23) study purpose was to examine publication trends and explore research hot spots of Internet health information seeking behavior through co-word clustering analysis. But there are scarcest studies that shed light on overall contribution of twitter publications in heath sector except one systematic review (but not bibliometric analysis) that highlighted the role of twitter in health care academic research (24). However, there was no comprehensive study found to integrate twitter role in health construct at a glance especially what are significant research dynamics (e.g., emerging research themes in this field).To cover this gap, this study reviewed twitter articles to highlight the key themes of health research under umbrella of twitter and allow us to answer following question:

- What are the most hot spot research themes in KMTH publications and how twitter is acting as a KM platform for health promotion according to co-occurrence analysis?

Methods

The development of this paper was based on bibliometric analysis and largely inspired by the methodology used in previous literatures (25–27). Bibliometric analysis can help researchers to identify the origins and the current significance of a given concept (28). This method has been applied to specific journals (29–32) and diverse disciplines, such as public health research (33), clinical development of drugs (34), social care data (35), prosumption (25,26), the risks of oral cancer with HIV/AIDS (36), disability related fields (37) and technology assisting people with dementia (38).

Data source and research process

To identify and retrieve relevant articles for inclusion, we employed a screening routine in Web of Science (WoS) as employed by Noor et al that allowed us to identify the best optimal research publications (27). WoS is a top quality database comprising top journals of basic Science, social science, arts and humanities disciplines (39). It contains more than 22,000 journals, 50 million publications data in 70 languages and 151 research categories (21). Therefore this study focused WoS top quality database despite of other research engines, such as Google Scholar, SCOPUS or Scientific Electronic Library Online (SciELO).

Inclusion criteria for related research articles

We started by query string for: topic: "twitter" AND topic: "health" in the WoS Core Collection database and got 1300 articles. This database covered timespan of all years (1985- mar 2019) and consisted of Science Citation Index Expanded (SCI-EXPANDED), Social Science Citation Index (SSCI) and Conference Proceedings Citation Index - Science (CPCI-S). As we were more interested to explore the KM contribution of twitter in health sector, therefore we refined the above query string with key worlds "information", "knowledge" and "awareness" and consequently got 695, 144 and 119 research articles respectively. From the previous literature we also found that E-health and M-health are emerging research concepts that are dramatically involving SM especially twitter in health promotion and knowledge seeking and disseminating activities (8,40,41). Therefore we searched for: topic: "e-health" OR topic: "ehealth" and refined by: topic: "twitter" and got 30 research articles. Finally, we also searched for: topic: "m-health" OR topic: "mhealth" and refined by: topic: "twitter" and got 12 research articles.

Exclusion criteria for related research articles

After this we extracted these five data files comprising of 695, 144, 119, 30 and 12 research articles from WoS in the form of plain text file and saved it into text document file. Now we have total 1000 articles but there might be some articles that may duplicate in different data set. To delete the duplication of the research articles, we imported these all file into Hiscite software and finally got 798 articles comprising all necessary information to conduct bibliometric analysis (title, abstract, authors' name, language used in writing paper, type of document, and cited reference used in the paper etc.). We imported these files in VOSviewer software to get a bibliographic mapping analysis. Form these outputs, authors explored the related research streams of twitter articles related to health in KM discipline.

Analytical tool used for data analysis

VOSviewer software has been used for data analysis. Pan et al (42) investigated 481 research articles that use HistCite and VOSviewer for bibliometric mapping. They found a significant upward trend in the use of these tools, but VOSviewer was used more frequently than HistCite (42). VOSviewer is widely used in bibliometric analysis, especially in thematic analysis, cartography, and cluster analysis (21,26). Five types of bibliometric mapping analysis can be used: named as co-author, co-occurrence of keywords, citation, bibliographic coupling, and co-citation through VOSviewer. In keyword analysis, VOSviewer utilizes a text-mining technique to analyze the content of titles, keywords, and abstracts. Furthermore, we applied co-occurrence as type of analysis and all keywords as unit of analysis to explore emerging themes in KMTH publications. As a consequence, we found different clusters of closely associated items (keywords in our study), which are denoted by the same color. The larger the item, the greater its significance and popularity with respect to the other items.

Results

Thematic analysis through co-occurrence keyword in KMTH publications

To find out different research hotspot in KMTH publication, this study conducted thematic analysis of 798 articles of KMTH articles through VOSviewer. We chose type of analysis as "co-occurrence" and unit of analysis as "Author keywords" in VOSviewer. Furthermore, we chose 15 minimum numbers of co-occurrence of a keyword as a threshold value and subsequently got 50 keywords out of 2685 words formulating four different clusters as shown in Fig. 1. The yellow cluster was merged with green cluster as indicating similar keywords and consequently three clusters were emerged named as; Cluster 1 (Red Cluster): Twitter as health education and health promotion platform; Cluster 2 (Green Cluster): Twitter as public health promotion platform; Cluster 3 (blue Cluster): Twitter as health sentiment platform through big data and machine learning.

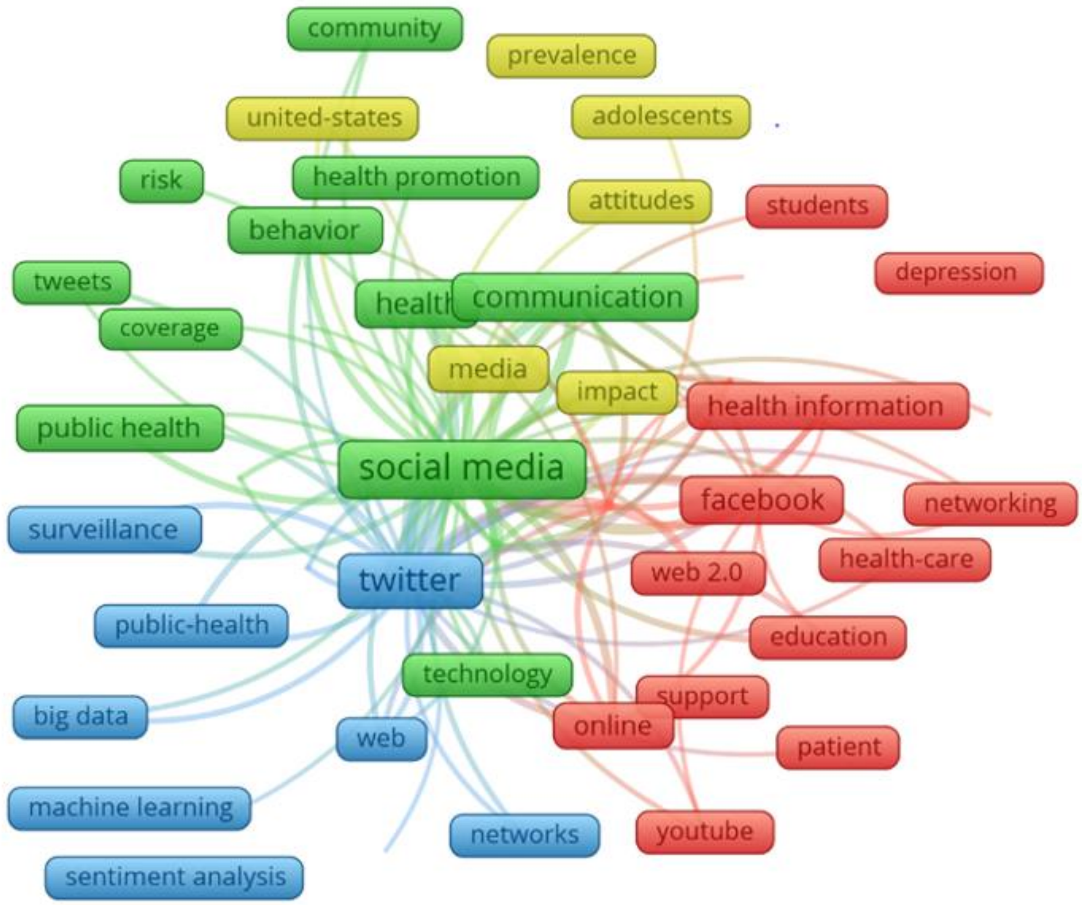

Fig. 1: Co-occurrence keyword analysis in KMTH publications

Discussion

Cluster 1 (Red Cluster): Twitter as health education and health promotion platform

In this cluster, health information, Facebook, YouTube, web 2.0, health care, education, online, support and networking were prominent keywords. This cluster depicted that web 2.0, Facebook, YouTube and twitter are providing online support for health seeking information and health care (43). How twitter is playing vital role was explained in dissemination of antibiotics information in CoPs (44). The potential of using SM was illustrated to conduct "Infodemiology" (science of determinants and distribution of information in an e-medium) studies for public health (45). Advantages of twitter were discussed in health information seeking behavior e.g. Low cost, rapid transmission through a wide community, and user interaction but the disadvantages may be blind authorship, lack of source citation, and presentation of opinion as fact (11). They also suggested health care providers should recognize the importance of twitter and its potential usefulness as health seeking and disseminating knowledge platform. Network and content analyses were utilized to examine the health-related conversations via Twitter hashtags (4). The presence of education keyword significantly depicted role of twitter in medical education e.g. pharmacy education (46), Kidney Disease Education (47), nurse education (48,49), e-cigarate education (50), sex education (51). Mainly this cluster represented overall contribution of twitter as knowledge sharing and knowledge disseminating platform in e-health. Furthermore, this cluster showed twitter is a great and impact creating platform for all types of e-health education.

Cluster 2 (Green Cluster): Twitter as public health promotion platform

In this cluster, public health, social media, health promotion, communication and behavior were prominent keywords. American Heart Association, American Cancer Society, and American Diabetes Association were selected as a sample and showed how these major health organizations are using twitter for health promotion and building relationships to encourage actions to resolve health issues (52). In the age of digitization, patient acceptance of SM in health care is dramatically increasingly (53). Health care professionals use twitter in CoPs that consequently facilitate professional networking and knowledge sharing (54). Breast cancer tweets were analyzed through comparative content analysis, posted by organizations-Susan G. Komen, U.S. News Health, Woman's Hospital, and Breast Cancer Social Media and found that twitter played significant role for breast cancer awareness among women (55). Tweets from the U.S. and U.K physicians were compared, to understand how both parties opinion differed with each other on e-cigs (56). Mainly this cluster represented overall contribution of twitter in health promotion in public health field. Furthermore, this cluster reflected not only virtual communities (CoPs) but also well-known organizations using tweets to spread health care awareness.

Cluster 3 (blue Cluster): Twitter as health sentiment platform through big data and machine learning

In this cluster twitter, surveillance, big data, machine learning and public health were prominent keywords. Surveillance and trends of twitter users were characterized for seeking and sharing information related to cardiac arrest in CoPs (57). Specially, in time-sensitive condition where initial treatment relies on public knowledge and response. A new syndromic monitoring method was suggested for mental health focused on SM data, which may complement traditional approaches by offering valuable additional disaster-related information (58). Machine learning approach was proposed for capturing concepts and trends on twitter via Query Expansion technique (59). A machine learning algorithm was developed to classify tweets and identify relevant marijuana tweets (60). An improved framework was introduced for influenza surveillance outbreaks by applying geographic information science (GIS) and data mining techniques on tweets (61). An advanced data-mining framework was used to retrieve twitter data for sentiment analysis to understand how geo located tweets can be used to explore the prevalence of healthy and unhealthy food across United States (62). Understanding of cancer-based networks were described (CoPs) in Twitter (63). A method was proposed for detecting the emotional reaction of patients about asthma on twitter and retrieved information was helpful for asthma's patients to avoid habits that could harm their health (64). This cluster mainly highlighted the worth and value of twitter data (big data) that flows in form of tweets in CoPs (networks). Research community utilizing this data to promote health care among public after extracting valuable information through different machine leaning techniques.

Limitations and future research

Twitter role in health is an emerging research, and it is a significantly offering its services for health promotion and for health seeking behavior platform. Our main limitation in this paper was that during co-occurrence mapping, we only considered publications with five minimum number of keywords respectively. Due to this reason several documents were excluded from analysis and their inclusion could have been proposed different results. Second, this study was only focused on articles extracted from WoS, so the articles in our study were from prestigious journals. A bias therefore might exist for high-quality publications, and non-WoS journal articles information was not shown in our analysis that might impact differently twitter role in health promotion. In a country analysis an important problem might be that many non-English speaking countries may publish also research in local languages and most of this research is not included in WoS. Therefore, these publications are not considered and usually not cited. This issue could also produce deviations in the results. However, considering the current world standards for research, the material published in WoS is sufficiently representative to be considered as a general sample in order to identify important results and conclusions.

Conclusion

Twitter as KM platform for health promotion was emerged in 2009. After that, it gained histrionic popularity as knowledge seeking, knowledge acquisition and knowledge disseminating platform for public health promotion by the time but still it has a long way to go. This study not only provided an overall contribution of the twitter research dynamics in KMTH academia but also examined the thematic analysis of KMTH publications at a glance. To find out different research hotspot in KMTH publication, this study conducted thematic analysis of 798 articles of KMTH articles in VOSviewer. Through this analysis 3 main cluster were emerged. Cluster 1 (Red Cluster): Twitter as health education and KM platform. Cluster 2 (Green Cluster): Twitter as public health promotion platform. Cluster 3 (blue Cluster): Twitter as sentiment analysis platform through big data and machine learning.

Ethical considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

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Conflict of interest

The authors declare that there is no conflict of interests.

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