

BIBLIOMETRIC STUDY OF ONLINE PATIENT SUPPORT GROUPS USING PUBMED**Vivek Pandey¹, Samrat Kumar Mukherjee^{2*}, Ajeya Jha³**^{1,2,3} Department of Management Studies, Sikkim Manipal Institute of Technology, Sikkim Manipal University, Sikkim-737136, India¹ ORCID ID : 0000-0002-0847-0512² ORCID ID : 0000-0002-8839-0140³ ORCID ID: 0000-0003-0491-5008

*Corresponding Author

ABSTRACT

Background: For a significant period, online patient support groups have served as platforms for disseminating health-related information and providing assistance. Their importance has further increased with the advent of the internet.

Objectives: This paper aims to achieve a deeper understanding of the literature concerning Online Patient Support Groups health information through the use of bibliometric analysis.

Methods: The study conducts a bibliometric analysis of Online Patient Support Groups using literature sourced from PubMed. It utilizes profile research networking software and Vosviewer from Harvard University.

Discussion: It is clear that Online Patient Support Groups hold greater importance for marginalized communities. Health care providers and regulators must be vigilant to prevent any negative consequences.

Conclusion: The findings underscore the significance of Online Patient Support Groups in public health, with video and audio content being more frequently cited than journal articles. Despite a notable increase in publications in 2020, the number of researchers in this field remains limited.

Keywords: Online Patient Support Groups, Online Advocacy Groups, Online Health Communities, Online Support Communities, bibliometric, Vosviewer.

Introduction

Online groups, also known as web-based groups, are utilized for health education and social support by both peer-led individuals and health professionals, as well as in interventions designed to change behavior. These online support groups can either operate in real-time or asynchronously, and offer similar therapeutic benefits to those provided by traditional face-to-face support groups. Research indicates that online education and behavior change interventions have resulted in improved health outcomes (Banbury et al., 2018). Historical support groups have been established for centuries, with their popularity increasing significantly in the mid-20th century through initiatives such as the 12 Steps movement and Alcoholics Anonymous, which demonstrated the importance of group support in assisting members in recovering from traumatic situations and achieve emotional well-being (Barak et al., 2018).

There are online support groups for almost every type of distress, from asthmatics to parents of autistic kids, hearing-impaired teens to parents of Alzheimer's patients, rape victims to dyslexic students, early

divorcees to people dying of a specific type of cancer, socially anxious adults to smokers trying to quit. For those who participate in an online support forum, the group serves as a reliable and responsible source of assistance through which they can share information, offer and receive emotional support, socialize and build relationships with others, and feel comradeship with those who are experiencing a similar distress. This reduces their perception of their situation as abnormal (Bane et al., 2005). A new online environment has emerged in the 2010s. An rising number of people are turning to the internet as their main source for health-related information (Prestin et al., 2015). The internet is regarded as a source of detailed knowledge, simple retrieval of specific information, and active communication for immediate responses. 35 percent of American individuals admitted using the internet to research a medical problem, either for themselves or for another else (Fareed et al., 2021).

Recent developments in online patient support group platforms allow cancer survivors to share their health data and experiences via their mobile and wearable health devices (Perales et al., 2016). Moreover, data gathered from these platforms is utilized to create a base of knowledge that can benefit future cancer sufferers (Fareed et al., 2021). Online health communities have proliferated recently as more people want to connect with others who have the same or comparable diseases and to acquire alternative sources of health information. Such communities are very prevalent, which demonstrates how well-liked they are among health consumers (Zhao et al., 2021).

Yet, because social media is becoming more and more popular, the Internet has developed into a prime environment for the dissemination of false information, including rumors, false reviews, and false news (Zhang and Ghorbani, 2019). Using social media, untrustworthy sources may quickly and wildly disseminate a lot of unsubstantiated information among individuals (Qazvinian et al., 2011). Thus, it is essential to create models that can quickly identify false information online.

Internet users who look for health-related material, from recommendations for a healthy lifestyle to information on disorders and treatments, are on the rise. The number of people who use the Internet to look for health information that covers everything from advice on leading healthy lifestyles to treatments and ailments is constantly increasing (Chu et al., 2017). The most recent national survey by Pew Research Center found that 72% of adult who uses internet seek for various health-related subjects online (Zhao et al., 2021).

Online Patient Support Groups have developed into a focal point in the digital age for people to communicate with one another by sharing, reading, or commenting on thoughts and material uploaded by other users (Anwar et al., 2019; Boyd et al., 2007). During the late 1990s, the usage of Online patient support group has increased dramatically. The dynamic nature of these platforms has contributed to their quick growth, and the design of these media has made it easier for users to build relationships with one another (Tajeuna et al., 2018; Elbanna et al., 2019). In addition, the purpose of establishing social networks and sharing information is to gain a deeper insight into health, whether in relation to individuals or society as a whole (Romano et al., 2018). Amongst these networks, young individuals are the ones who are most connected digitally, both as active participants and observers (Cohen et al., 2018). However, teenagers and young adults are at a crucial stage of life where their self-perception as well as healthy and unhealthy behaviors are molded (Dokuka et al., 2018; Villanti et al., 2017).

According to (Cope et al., 1995), support groups serve various purposes, including patient education, which can be achieved through sharing information among patients, distribution of brochures and online

resources, and organizing meetings. Another significant function is to share the illness experience, which helps patients develop improved coping strategies (Spiegel et al., 1981) and reduces anxiety levels (Schou et al., 2008). Finally, support groups offer emotional support, build confidence, and empower members to face their medical condition, which can provide them with a sense of strength and resilience (Hu, 2017). It has become more common for Americans to search the internet for health information, with 80% of internet users doing so, according to (Fox, 2011). More recently, social media platforms focused on health, including patient blogs, online support groups, and health-focused networking sites, have emerged as popular sources of health information. (Chung, 2014) reports that around 33% of those who search for health information online also utilize these social media resources. It is anticipated that the number of individuals seeking health-related information and assistance from other patients through online social media will continue to increase (Fox & Purcell, 2010; Jupiter Research, 2007; Sarasohn-Kahn, 2008, 2009).

Research Methodology

The research is based on bibliometric analysis.

Bibliometrics is a quantifiable and objective informatic technique that examines the knowledge structure and emerging trends in a specific subject area. This approach, as described by Kreps et al. (2013), allows researchers and stakeholders to obtain reproducible and valuable data, leading to an informed understanding of the subject field and facilitating interdisciplinary cooperation (Niu et al., 2014). Bibliometrics refers to the application of statistical methods for determining the content and volume of various publications, including books and papers (Sweileh et al. , 2017; Durieux & Gevenois, 2010). It's been used in crisis analysis (Jiang et al., 2019; Ardito et al. , 2019; Lee and Kim, 2016; Chiu & Ho, 2007; Sweileh, 2019) and information management (Du et al., 2017; Cobo et al., 2007; Chao et al. , 2007). This research article uses Bibliometric analysis to analyze online patient support groups research articles in Indian health statistics; co-citation information analysis, examination of co-occurrence, and other associated study of previous literature.

A bibliometric analysis was done using the VOSviewer software. The Profile research networking software from Harvard University is the software used for conducting bibliometric analysis, but there are other available software options such as PROFILES from UMassMed Center for Clinical and Translational Research. These software options analyze publications, grouping important ideas and various research fields. Profile research networking software from Harvard University provides an easily accessible open database of publication history, which self-populates. This has been utilized by researchers like (GM Weber, 2011) and (Alireza Ahmadvand, 2019). Furthermore, we have utilized Vosviewer as a software tool to perform bibliometric analysis. The main purpose of VOSviewer is to analyze bibliometric networks, such as creating maps of publications, authors or journals based on citation, co-citation or bibliographic coupling network, or creating maps of keywords based on a co-occurrence network. Nevertheless, the utilization of VOSviewer is not confined to bibliometric networks. It can be applied to create maps based on any network type (Van and Waltman, 2011). VOSviewer has the ability to mine text, which enables the creation and exhibition of co-occurring networks containing important phrases that have been extracted from scientific materials. The time frame of this study is from 2000 to 2022. The keywords which has been used to search in the Pubmed

are online patient support groups, Homophily, Perceived social support, Perceived Empathy and Patient empowerment. The initial phase involved excluding non-English documents from the database, and any papers that were missing full text were also eliminated. Hence, a definitive list of 321 documents that was used as the foundation for the bibliometric analysis. The most common three-word summaries or acronyms are Online Patient Support Groups, Online Health Communities and Social Support Groups. With regard to this analysis, we used the keyword "online patient support groups". The study's inclusion criteria are depending on the terms 'online patient support groups', 'Health communities'. The terms were used to examine the Impact of online patient support groups on patient empowerment, keeping the objective of the study in mind.

Summary Report

Search Strategy

This article focuses on publications that were selected from the PubMed database and comprised research studies related to "Online Patient Support Groups", spanning from January 2000 to December 2022.

Sampling

The Pubmed database covers Medline, dentistry journals, and nursing journals. When the word "Online Patient Support Groups" was searched in the PubMed database, a total number of 1000 documents were found. Only English-language papers were taken into consideration.

Data Analysis

Table I : Publication and Citation by Year

PublicationType	NumPublications	%Pubs	FirstYear	LastYear	AvgCitations	ExpCitations	RatioCitations
Journal Article	4123	99.254	2000	2022	12.985	11.136	1.166
Research Support, Non-U.S. Gov't	2492	59.99	2000	2022	14.844	12.74	1.165
Randomized Controlled Trial	752	18.103	2000	2022	17.961	16.672	1.077
Research Support, N.I.H., Extramural	669	16.105	2005	2022	25.616	22.499	1.139
Multicenter Study	329	7.92	2001	2022	20.568	18.862	1.09
Review	224	5.392	2000	2022	30.629	25.882	1.183
Comparative Study	197	4.742	2001	2022	17.579	16.913	1.039
Systematic Review	168	4.044	2004	2022	26.298	21.685	1.213
Meta-Analysis	98	2.359	2003	2022	33.735	24.005	1.405
Research Support, U.S. Gov't, P.H.S.	95	2.287	2001	2022	14.337	15.443	0.928
Clinical Trial	91	2.191	2000	2022	23.89	23.012	1.038
Clinical Trial Protocol	75	1.805	2018	2022	1.24	1.227	1.01

Observational Study	70	1.685	2012	2022	9.314	8.013	1.162
Research Support, U.S. Gov't, Non-P.H.S.	63	1.517	2007	2022	18.476	19.1	0.967
Evaluation Study	49	1.18	2002	2020	43.633	31.158	1.4
Clinical Trial, Phase II	42	1.011	2012	2022	33.619	32.354	1.039
Validation Study	39	0.939	2009	2021	27.795	19.662	1.414
Clinical Trial, Phase III	29	0.698	2005	2021	57.724	50.122	1.152
Research Support, N.I.H., Intramural	25	0.602	2007	2022	20.64	22.182	0.93
Consensus Development Conference	24	0.578	2010	2021	99.042	102.882	0.963
Letter	17	0.409	2015	2022	10.294	7.882	1.306
Pragmatic Clinical Trial	17	0.409	2013	2022	7.412	9.309	0.796
Practice Guideline	12	0.289	2010	2021	59.083	57.069	1.035
Controlled Clinical Trial	10	0.241	2000	2019	16	16.979	0.942
Editorial	6	0.144	2011	2020	296.833	160.303	1.852
Clinical Trial, Phase I	6	0.144	2013	2021	4.667	7.897	0.591
Comment	5	0.12	2011	2021	12.2	9.193	1.327
Case Reports	4	0.096	2015	2021	4	11.325	0.353
Equivalence Trial	3	0.072	2018	2020	8	8	1
Clinical Trial, Phase IV	3	0.072	2014	2020	6.667	6.667	1
Clinical Study	3	0.072	2020	2022	1.667	1.667	1
Historical Article	2	0.048	2015	2019	268	263.167	1.018
Retracted Publication	2	0.048	2006	2018	11.5	11.5	1
Guideline	2	0.048	2017	2022	5	5	1
Webcast	1	0.024	2015	2015	115	115	1
Overall	1	0.024	2016	2016	36	36	1
Congress	1	0.024	2016	2016	36	36	1
News	1	0.024	2011	2011	7	7	1
Dataset	1	0.024	2014	2014	1	1	1
Video-Audio Media	1	0.024	2018	2018	1	1	1
English Abstract	1	0.024	2013	2013	0	0.409	0

For every year, Table I displays the following information: the amount of articles published (NumPubs),

the number of times any article was referenced in that year (including self-references) (NumCitesAll), the number of times any article was referenced in that year (excluding self-references) (NumCites), the total number of publications up to that year (CumPubs), the total number of references to any article up to that year (including self-references) (CumCitesAll), and the total number of references to any article up to that year (excluding self-references) (CumCites). The Picture have all the clear ideas about the Evaluation study.

Table II : Top Journals Publication & Citation by Year

Journal	NumP ubs	%Pu bs	FirstY ear	LastY ear	AvgCit es	ExpCit es	RatioCi tes	ExpCite sPT	RatioCite sPT
PLoS One	314	7.55 9	2007	2022	10.51	8.833	1.19	9.598	1.095
J Med Internet Res	245	5.89 8	2001	2022	23.35 9	22.44 7	1.041	24.845	0.94
BMJ Open	212	5.10 4	2011	2022	3.066	3.09	0.992	3.011	1.018
J Clin Oncol	122	2.93 7	2010	2021	65.56 6	33.80 7	1.939	57.011	1.15
Trials	77	1.85 4	2011	2022	4.818	4.719	1.021	4.629	1.041
Int J Environ Res Public Health	60	1.44 4	2016	2022	1.867	2.151	0.868	1.684	1.109
Cochrane Database Syst Rev	59	1.42	2004	2021	31.93 2	18.75 4	1.703	19.187	1.664
J Alzheimers Dis	59	1.42	2019	2022	1.068	1.839	0.581	1.564	0.683
BMC Health Serv Res	53	1.27 6	2005	2022	6.906	6.997	0.987	6.57	1.051
Biomed Eng Online	43	1.03 5	2007	2022	7	4.63	1.512	8.191	0.855

Table II displays information on the quantity of published journals (NumPubs) and their respective proportion of all published materials (percentage of pubs). It is evident that the 'Public Library of Science' boasts a greater number of publications. However, the 'Journal of Clinical Oncology' has the highest average citation ratio.

Table III : Summary Statistic for the Selected Collection of Pubmed IDs

Variable	Value
NumPubs	4154
FirstYear	2000
LastYear	2022
AvgAuthors	9.233
ExpAuthors	6.473
RatioAuthors	1.426
AvgCitesAll	15.971
AvgCites	13.371
ExpCites	8.428
RatioCites	1.587
ExpCitesPT	11.329
RatioCitesPT	1.18
HIndex	95
MIndex	7.917

Table III displays the summary statistics for the chosen set of PubmedIDs. The predicted outcome is contrasted to the mean number of writers for each paper and the average occurrence of citation for such papers. The anticipated values are the norms of all PubMed articles that are associated with the journal and year of publication. The NumPubs is the number of PubmedIDs that have been acknowledged, First Year is the Article's first year, Last Year is the most recent article year, AvgAuthors is the Number of writers per article on average, ExpAuthors is the number of expected writers, matched to the journal and the year, RatioAuthors is the ratio of the average number of writers to the predicted number, AvgCitesAll is the article's average number of citations, including self-citations, AvgCites is the Average amount of citations per article, excluding self-citations, ExpCites is the Estimated number of citations for a paper, excluding self-citations, based on journal and year, RatioCites is the ratio of the average number of citations (excluding self-citations) to the projected number, based on journal and year, ExpCitesPT is the number of citations expected (no self-citations), based on year, journal and publication type, RatioCitesPT is the ratio of average citations to projected citations, matched by journal, year, and kind of publication (no self-citations), HIndex is the Hirsch-index (considering total citations, including self-citations), MIndex is the Hirsch-index divided by the number of years since the initial publication.

The type of publication is also influenced by the "PT" projected values. Selfcitations (an author referencing his or her own work) are not considered in the analysis unless clearly mentioned. For each journal, the number of publications (NumPubs) and the total publications (%) percentage are shown. The citation variables have the same meaning as the overall summary table.

Top Fields/Disciplines

The area of study is identified based on the general topics covered in each journal, which are categorized as MeSH(Medical Subject Heading) Descriptors by NLM(National Library of Medicine). These descriptors gives a brief description of the primary subjects covered in the journal. As a journal may have more than one descriptor assigned to it, a single publication could be listed multiple times in the provided table. Hence, the total amount of published works may exceed the NumPubs field value. The RatioExpPubs field indicates the ratio of publications within the discipline compared to the expected number, adjusted for the year.

Overall Summary

Below are statistical data for the specified set of PubmedIDs. The typical quantity of authors per article and the frequency of citations for these articles are evaluated against a predicted value. Predicted values refer to the mean figures for all articles in PubMed, which are sorted by journal and year of publication. The "PT" expected values also control for publication type. Self-referencing (an author referencing his or her own work) are excluded from the analysis except where explicitly noted. In Medine/PubMed, multiple publication types can be assigned to the same article. When calculating "PT" values, articles are matched on all publication types. To clarify, if an article is categorized as "Abstract; Multicenter Study; Clinical Trial," it will only be compared to articles that have identical types. Consequently, when analyzing the "PT" values, one must consider that there may be a limited number of publications that share the same journal, year, and publication types, which could influence the outcomes unfairly.

Table IV : Top Fields/Disciplines by number of Publications

Fields	Num Pubs	%P ubs	RatioEx pPubs	First Year	Last Year	AvgC ites	ExpC ites	Ratio Cites	ExpCitesPT	RatioCitesPT
Medicine	865	16.954	2.56	2000	2022	11.254	7.841	1.435	9.097	1.237
Medical Informatics	381	7.468	13.124	2001	2022	18.383	17.169	1.071	19.053	0.965
Science	339	6.644	1.683	2007	2022	12.463	8.806	1.415	9.894	1.26
Neoplasms	333	6.527	2.028	2002	2022	37.67	18.399	2.047	33.528	1.124
Public Health	245	4.802	2.395	2002	2022	6.902	5.09	1.356	5.735	1.203
Health Services Research	224	4.39	8.672	2002	2022	13.902	10.476	1.327	10.107	1.375
Neurology	205	4.018	1.23	2002	2022	9.439	5.439	1.736	8.096	1.166
Psychiatry	141	2.764	1.972	2003	2022	16.057	7.289	2.203	11.138	1.442
Therapeutics	129	2.528	2.934	2007	2022	7.806	5.284	1.477	6.308	1.237
Health Services	96	1.882	2.343	2003	2022	8.448	5.493	1.538	8.289	1.019

Table IV clearly indicates that the field of 'Medicine' has a significantly higher number of published works, while 'Psychology' had a delayed start in this realm. The discipline of 'Psychiatry' boasts the highest average citation rate.

Table V : Publication and citation by year

PubYear	NumPubs	NumCitesAll	NumCites	CumPubs	CumCitesAll	CumCites
2022	381	8156	7101	4154	66343	55545
2021	685	14210	12171	3773	58187	48444
2020	519	10091	8533	3088	43977	36273
2019	379	7455	6124	2569	33886	27740
2018	357	6325	5212	2190	26431	21616

2017	237	5506	4497	1833	20106	16404
2016	279	4348	3549	1596	14600	11907
2015	328	3102	2487	1317	10252	8358
2014	255	2213	1838	989	7150	5871
2013	220	1639	1306	734	4937	4033
2012	128	1070	880	514	3298	2727
2011	101	705	571	386	2228	1847
2010	74	507	418	285	1523	1276
2009	46	321	267	211	1016	858
2008	32	236	200	165	695	591
2007	35	128	116	133	459	391
2006	19	115	106	98	331	275
2005	20	82	69	79	216	169
2004	20	74	47	59	134	100
2003	15	31	27	39	60	53
2002	14	18	15	24	29	26
2001	4	7	7	10	11	11
2000	6	0	0	6	4	4
1987	0	1	1	0	4	4
1979	0	1	1	0	3	3
1978	0	1	1	0	2	2
1975	0	1	1	0	1	1

Table V presents the yearly quantities of articles (NumPubs), citations received by any article in that year (NumCitesAll), including self-citations (CumPubs), the amount of years where no articles are cited in the same time frame (NumCites), the complete total of referenced articles, with self-citations included (CumCitesAll), the accumulation of publications cited in that year (CumCitesAL), and the cumulative citations (CumCites).

Fig. I Network Visualization for the keywords

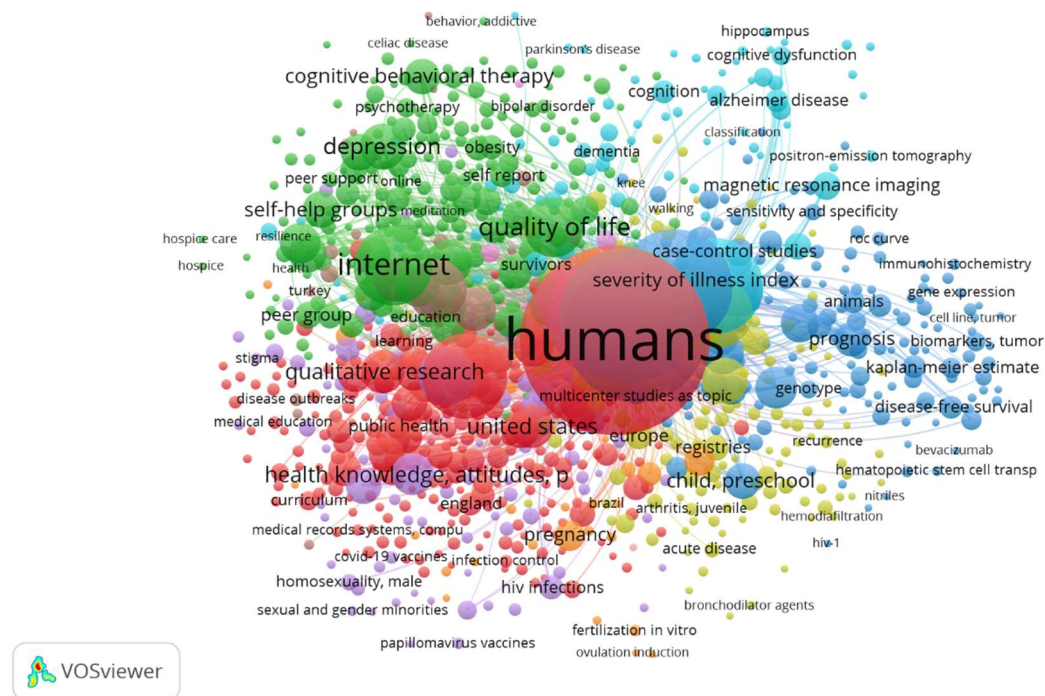


Figure I displays the outcome of the authors' keyword network visualization analysis, which was conducted using VOSviewer - a software known for its ability to generate, analyze, and explore both network and bibliometric data maps (Van Eck & Waltman, 2009, 2013). In order to normalize the effects and improve the accuracy of the relation, (Rodriguez et al. 2016) advised the use of fractional counting and general sensitivity. Van Eck and Waltman data was utilized to analyze (Pai and Alathur, 2019).

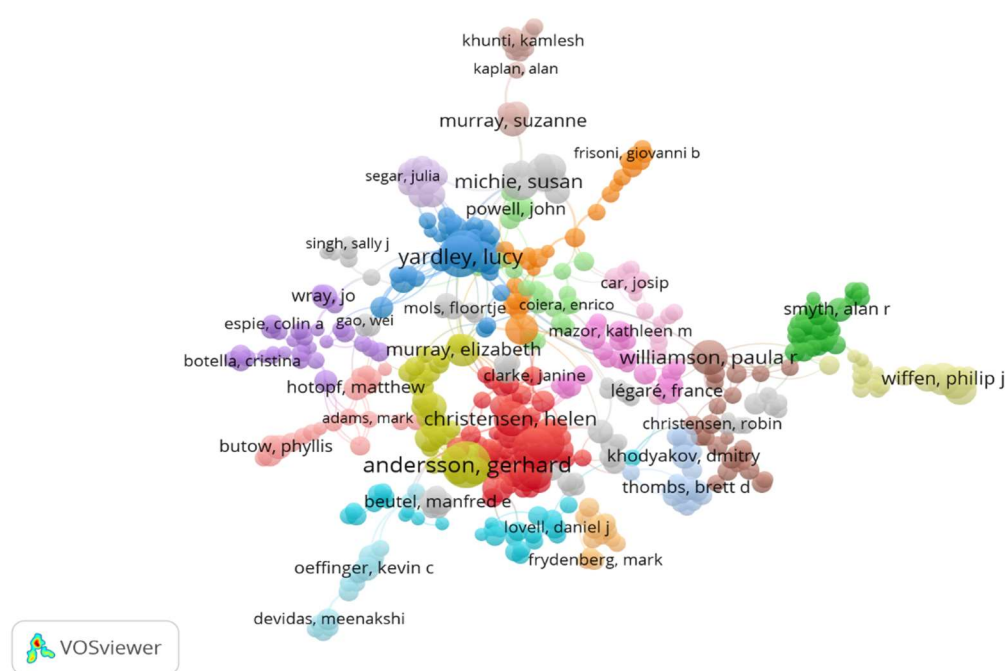
The frequency of the keyword is represented by the area of the circle in Figure I. A larger diameter indicates that the keyword is more frequently used in Online posts about the Journals of health information. The space between the circles indicates the similarity of topic's and relative strength. In this study, Keywords like humans, Internet, Survey and question, middle-aged treatment outcome, quality of life, Covid-19, Male, have higher weightage.

The network visualization map displayed in fig. has the red cluster consist of humans, Survey and question, U.S., Qualitative research, Focussed group, Health personnel, Preventive health service, Physicians practice patterns, Delivery of health care, Primary health care, Communication, Hospitalization, England, Health knowledge, Attitude of patients etc. The green cluster consist of Internet, Quality of life, Self-help groups, Obesity, Cognitive behavioural therapy, Depression, Feasibility Studies, Tele medicine, Mental health, Peer group, Computer assisted therapy, Diabetes mellitus (type2), Cardial disease, Social media etc. The brown cluster consist of Covid-19, SARs, Pandemic, Turkey, Disease outbreak, Obsessive compulsive disorder, Health care workers etc. The orange cluster consist of Infant, Pregnancy, Newborn, Epidemiology, Community networks, Ovulation

induction, Fertilization in vitro, Reproductive techniques etc.

The blue cluster consist of Middle-aged, Child, Breast neoplasms, Prognosis, Biomarkers tumor, Retrospective study, Risk factors, Reproductivity of results, Animals, Gene expression profiling, Antineoplastic, Combined chemotherapy, Disease free survival, Receptor erbB2, Antineoplastic agents etc. The purple consist of Health knowledge and attitude of patients, Patient acceptance of health communication, Homosexuality (male), Vaccination, Electronic mail, Students, Parents, Universities, HIV Infection, Papillomavirus infections, Patient selection, Mass screening, Cross-sectional studies, Health education etc. The yellow consist of Prospective studies, Treatment outcome, Double blind method, Registries, Asthma, Acute disease, Single blind method, Osteoarthritis, Europe, Kidney, Drug therapy combination, Safety, Prednisone, Renal replacement theory etc. The sky blue consist of Aged, Male, Magnetic resonance imaging, Brain, Cognition, Alzheimer disease, Cognitive dysfunction, Biomarkers, Positron emission tomography, Parkinson disease, Semantics dementia etc.

Fig. II Co-citation analysis



The requirement is met by 34008 authors, with the minimum number of documents per author being 1 [100% - As Before].

For each of the 34008 authors, the total strength of the co-authorship links with other authors will be calculated. The selection process will prioritize the authors with the strongest co-author partnerships.

The number of author to be chosen – 100.

The Co-Citation analysis in Fig. II has 12 clusters. The first cluster led by Andersson Gerhard, Ijotsson Brjann, Mataix-Cols David, Logan Stuart, Murray Elizabeth, Marston Lousie, Lin defors Nils, Hunter

Rachael, Morris Christopher. The second cluster led by Mccrone Paul, Moss-Morris Rona, Syred, Jonathan, William Hywel C, Sach Tracey h, Bosteck Jennifer, Bedson Emma, Roberts Amanda, Steele Mary, Campbell John, Yardley Lucy, Murray Suzanne, Kaplan Alan, Khunti Kamlesh, Lazure Patrice, Rekha Chaudhuri, Heaney Liam G, Williamson Paula R, Gargon Elizabeth, Akram Athena, Clarke Mike, Geemen Rinie, Dougados Maxime, De Wit Marteen, Kirkham Jamie J, Harman Nicola and Stacey Dawn. The third cluster led by Ritterband Lee M, Kailestad Havard, Fretheim Atle, Frydenberg Mark, Thorndike Frances etc. The forth cluster led by Wiffen Philip. J, Needham dale. M, Elliot Dong, Fan Eddy, Azouliv Elie, Balzer Felix, Moorer Andrew, Heathcote Lauren C etc. The fifth cluster led by Large Shirley, Mont, Wravjo, Brown Katherine, Espie Colin A, Correll Christophu, Sin Jacqueline, Henderson Clarie, Sara Grant, Nielsen Emma, Gunnell David, Mittendorfer-Rutz Elienor etc. The Six cluster led by Li, Linda C, Khodyakov Dmitry, Thombs Brett D, Hagedoorn Mariet, Carrier Marie-Eve, Suarez-Almazor Maria E etc

The Seventh cluster led by Hunger Stephen P, Devidas Meenakshi, Armenian Saroh, Oeffinger Kevic C, Heesen Christoph, Galea Ian, Michael Benedict, Solomon Tom, Irani Saroshr, Benseler Susanne M, Ozdogan Huri, Ozen Seza, Nielsen Susan, Russo Ricardo etc. The eight cluster led by Shaw Joanne, Shepherd Heather, Butow Phyllis, Grimison Peter, Ostrovnya Irina, Lee William, Breen Gerome, Hotopf Matthew, Polling Catherine, Carr Ewan, Lamb Danielle, Zammit Stan, Adams Mark, Fizazi Karim etc. The nine cluster led by Trevena Lyndal, Barlow Stewart Kristine, Meiser Betlina, Vander Weijden Trudy, Han Paul KJ, Mazor Kathleen M, Durand Marie-Anne, Mccaffery Kirsten, Car Josip, Darzi Ara, Kyaw Bhone Myint, Nessler Katarzyna, Trevena Lyndal, Peate Michelle, Witterman Holly O, Legare France etc. The tenth cluster led by Smith Louise E, Michie Susan, Potts Henry W W, Rubin G James, Gibbs Jo, Fear Nicola T etc. The eleventh cluster led by Gordson Caroline, Singh Sally J, Brimicombe James, Naughton Felix etc. The twelve cluster led by Rowbotham, Nicola J, Bersten Andrew, Chew Derek P, Yeh Hung-I, Gathercole Katie, Smyth Atan R, Povia Pedro, Tong Allison etc.

Conclusion

The objective of this paper is to explore the various patterns and developments concerning research on Online Patient Support Groups pertaining to the Patients and health. This exploration encompasses prevalence, subject matter, worldwide spread, and the groups of researchers actively involved. From the study, we find that the maximum number of journal article has been published in the year 2022 (Table I). Online Patient Support Groups play an important role when compared to public health. Table II shows that Public Library Of Science boasts a greater number of publication and the Journal of Clinical Oncology has the highest average citation ratio. Table III shows that the majority of publications that promote Online Patient Support Groups tend to be academic journals likely due to the fact that journals are the most common form of scholarly communication. Table IV indicates that the field of 'Medicine' has significantly have higher number of published works. Table V shows that the maximum number of articles Published and Cited in the year 2021, may be due to COVID. Fig I shows that the keywords like humans, quality of life, male, internet, survey and questions, COVID-19 have higher weightage.

Although there was relative stability in the trajectory of significant research for the first thirty years analyzed, there was a marked increase between 2003 and 2018 that coincided with the rise in online social networks popularity, particularly among young individuals (Ilakkuvan et al., 2019). During this

same time period, the concept of utilizing technology to remotely follow or assist patients also emerged and gained traction (Hulsman et al., 2015). Consequently, Online Patient Support Groups has been used as a support system for chronic disease patients and to obtain input from patients (Li et al., 2019; Nereim et al., 2019).

Research Gap and Future Scope

There are some limitations to the research. Firstly, it solely examined papers from 'PubMed' indexed publications while disregarding articles from alternative sources. Secondly, only literature in the English language was considered, which may limit the comprehensiveness of the study. These factors could potentially affect the overall reliability and validity of the study results (Muller et al., 2018). Thirdly, the keyword for this review was "Online Patient Support Groups" but future researchers could benefit from exploring databases beyond PubMed or using newer keywords like "Facebook Patient Support Groups" or "Peer to Peer Patient Support Groups" for more in-depth analysis. Lastly, comparing different regions could provide valuable insights into geographic differences.

References

1. Banbury, A., Nancarrow, S., Dart, J., Gray, L., & Parkinson, L. (2018). Telehealth interventions delivering home-based support group videoconferencing: systematic review. *Journal of medical Internet research*, 20(2), e8090.
2. Barak, A., Boniel-Nissim, M., & Suler, J. (2008). Fostering empowerment in online support groups. *Computers in human behavior*, 24(5), 1867-1883.
3. Bane, C. M., Haymaker, C. M., & Zinchuk, J. (2005). Social support as a moderator of the big-fish-in-a-little-pond effect in online self-help support groups 1. *Journal of Applied Biobehavioral Research*, 10(4), 239-261.
4. Prestin, A., Vieux, S. N., & Chou, W. Y. S. (2015). Is online health activity alive and well or flatlining? Findings from 10 years of the Health Information National Trends Survey. *Journal of health communication*, 20(7), 790-798.
5. Fareed, N., Swoboda, C. M., Jonnalagadda, P., & Huerta, T. R. (2021). Persistent digital divide in health-related internet use among cancer survivors: Findings from the Health Information National Trends Survey, 2003–2018. *Journal of Cancer Survivorship*, 15(1), 87-98.
6. Perales, M. A., Drake, E. K., Pemmaraju, N., & Wood, W. A. (2016). Social media and the adolescent and young adult (AYA) patient with cancer. *Current hematologic malignancy reports*, 11(6), 449-455.
7. Zhao, Y., Da, J., & Yan, J. (2021). Detecting health misinformation in online health communities: Incorporating behavioral features into machine learning based approaches. *Information Processing & Management*, 58(1), 102390.
8. Zhang, X., & Ghorbani, A. A. (2020). An overview of online fake news: Characterization, detection, and discussion. *Information Processing & Management*, 57(2), 102025.

9. Qazvinian, V., Rosengren, E., Radev, D., & Mei, Q. (2011, July). Rumor has it: Identifying misinformation in microblogs. In *Proceedings of the 2011 conference on empirical methods in natural language processing* (pp. 1589-1599).
10. Chu, J. T., Wang, M. P., Shen, C., Viswanath, K., Lam, T. H., & Chan, S. S. C. (2017). How, when and why people seek health information online: qualitative study in Hong Kong. *Interactive journal of medical research*, 6(2), e7000.
11. Anwar, M. M., Liu, C., & Li, J. (2019). Discovering and tracking query oriented active online social groups in dynamic information network. *World Wide Web*, 22, 1819-1854.
12. Boyd, D. M., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. *Journal of computer-mediated Communication*, 13(1), 210-230.
13. Tajeuna, E. G., Bouguessa, M., & Wang, S. (2018). Modeling and predicting community structure changes in time-evolving social networks. *IEEE Transactions on Knowledge and Data Engineering*, 31(6), 1166-1180.
14. Elbanna, A., Bunker, D., Levine, L., & Sleigh, A. (2019). Emergency management in the changing world of social media: Framing the research agenda with the stakeholders through engaged scholarship. *International Journal of Information Management*, 47, 112-120.
15. Romano, V., Shen, M., Pansanel, J., MacIntosh, A. J., & Sueur, C. (2018). Social transmission in networks: global efficiency peaks with intermediate levels of modularity. *Behavioral ecology and sociobiology*, 72, 1-10.
16. Cohen, R., Newton-John, T., & Slater, A. (2018). 'Selfie'-objectification: The role of selfies in self-objectification and disordered eating in young women. *Computers in Human Behavior*, 79, 68-74.
17. Dokuka, S., Krekhovets, E., & Priymak, M. (2018). Health, grades and friendship: How socially constructed characteristics influence the social network structure. In *Analysis of Images, Social Networks and Texts: 6th International Conference, AIST 2017, Moscow, Russia, July 27-29, 2017, Revised Selected Papers 6* (pp. 381-391). Springer International Publishing.
18. Villanti, A. C., Johnson, A. L., Ilakkuvan, V., Jacobs, M. A., Graham, A. L., & Rath, J. M. (2017). Social media use and access to digital technology in US young adults in 2016. *Journal of medical Internet research*, 19(6), e196.
19. Cope, D. G. (1995). Functions of a breast cancer support group as perceived by the participants: an ethnographic study. *Cancer Nursing*, 18(6), 472-478.
20. Spiegel, D., Bloom, J. R., & Yalom, I. (1981). Group support for patients with metastatic cancer: A randomized prospective outcome study. *Archives of general psychiatry*, 38(5), 527-533.
21. Schou, I., Ekeberg, O., Karesen, R., & Sorensen, E. (2008). Psychosocial intervention as a component of routine breast cancer care—who participates and does it help?. *Psycho-Oncology: Journal of the Psychological, Social and Behavioral Dimensions of Cancer*, 17(7), 716-720.
22. Hu, A. (2017). Reflections: the value of patient support groups. *Otolaryngology-Head and Neck Surgery*, 156(4), 587-588.

23. Fox, S. (2011). Health topics. Washington, DC: Pew Internet & American Life Project.
24. Chung, J. E. (2014). Social networking in online support groups for health: how online social networking benefits patients. *Journal of health communication*, 19(6), 639-659.
25. Fox, S., & Purcell, K. (2010). *Chronic disease and the internet*. Washington, DC: Pew Internet & American Life Project.
26. Levy, M., Matiesanu, C., Mitskaviets, I., Riley, E., & Daniels, D. (2007). Online health: assessing the risk and opportunity of social and one-to-one media. *Jupiter Research*, 2.
27. Sarasohn-Kahn, J. (2008). The wisdom of patients: Health care meets online social media.
28. Sarasohn-Kahn, J. (2009). *Participatory health: Online and mobile tools help chronically ill manage their care*. California HealthCare Foundation.
29. Kreps, G. L., & Neuhauser, L. (2013). Artificial intelligence and immediacy: designing health communication to personally engage consumers and providers. *Patient education and counseling*, 92(2), 205-210.
30. Niu, B., Hong, S., Yuan, J., Peng, S., Wang, Z., & Zhang, X. (2014). Global trends in sediment-related research in earth science during 1992–2011: a bibliometric analysis. *Scientometrics*, 98(1), 511-529.
31. Durieux, V., & Gevenois, P. A. (2010). Bibliometric indicators: quality measurements of scientific publication. *Radiology*, 255(2), 342-351.
32. Sweileh, W. M., Al-Jabi, S. W., AbuTaha, A. S., Zyoud, S. E. H., Anayah, F. M., & Sawalha, A. F. (2017). Bibliometric analysis of worldwide scientific literature in mobile-health: 2006–2016. *BMC medical informatics and decision making*, 17, 1-12.
33. Ardito, L., Scuotto, V., Del Giudice, M., & Petruzzelli, A. M. (2019). A bibliometric analysis of research on Big Data analytics for business and management. *Management Decision*, 57(8), 1993-2009.
34. Chiu, W. T., & Ho, Y. S. (2007). Bibliometric analysis of tsunami research. *Scientometrics*, 73(1), 3-17.
35. Jiang, Y., Hu, R., & Zhu, G. (2019). Top 100 cited articles on infection in orthopaedics: a bibliometric analysis. *Medicine*, 98(2).
36. Jaeyoon Lee, & Sujeong Kim. (2016). Econometric analysis of domestic disaster-related research trends. *Journal of Information Management*, 33(4), 103-124.
37. Sweileh, W. M. (2019). A bibliometric analysis of health-related literature on natural disasters from 1900 to 2017. *Health Research Policy and Systems*, 17, 1-11.
38. Chao, C. C., Yang, J. M., & Jen, W. Y. (2007). Determining technology trends and forecasts of RFID by a historical review and bibliometric analysis from 1991 to 2005. *Technovation*, 27(5), 268-279. DOI: <https://doi.org/10.1016/j.technovation.2006.09.003>
39. Cobo, M. J., Martínez, M. Á., Gutiérrez-Salcedo, M., Fujita, H., & Herrera-Viedma, E. (2015). 25 years at knowledge-based systems: a bibliometric analysis. *Knowledge-based systems*, 80, 3-13.
40. Du, H. S., Ke, X., Chu, S. K., & Chan, L. T. (2017). A bibliometric analysis of emergency management using information systems (2000-2016). Online Information Review. DOI: <https://doi.org/10.1108/OIR-05-2017-0142>

41. Weber, G. M., Adams, W. G., Bernstam, E. V., Bickel, J. P., Fox, K. P., Marsolo, K., ... & Mandl, K. D. (2017). Biases introduced by filtering electronic health records for patients with “complete data”. *Journal of the American Medical Informatics Association*, 24(6), 1134-1141.
42. Ahmadvand, A., Kavanagh, D., Clark, M., Drennan, J., & Nissen, L. (2019). Trends and visibility of “digital health” as a keyword in articles by JMIR publications in the new millennium: Bibliographic-bibliometric analysis. *Journal of medical Internet research*, 21(12), e10477.
43. van Eck, N. J., & Waltman, L. (2011). VOSviewer manual. *Manual for VOSviewer version, 1(0)*.
44. Van Eck, N., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *scientometrics*, 84(2), 523-538.
45. Van Eck, N. J., & Waltman, L. (2013). VOSviewer manual. Leiden: Univeriteit Leiden, 1(1), 1-53.
46. Perianes-Rodriguez, A., Waltman, L., & Van Eck, N. J. (2016). Constructing bibliometric networks: A comparison between full and fractional counting. *Journal of informetrics*, 10(4), 1178-1195.
47. Pai, R. R., & Alathur, S. (2019). Predicting Mobile Health Technology Acceptance by the Indian Rural Community: A Qualitative Study. *International Journal of Electronic Government Research (IJEGR)*, 15(4), 37-62. DOI: <https://doi.org/10.4018/IJEGR.2019100103>
48. Ilakkuvan, V., Johnson, A., Villanti, A. C., Evans, W. D., & Turner, M. (2019). Patterns of social media use and their relationship to health risks among young adults. *Journal of Adolescent Health*, 64(2), 158-164.
49. Hulsman, R. L., & van der Vloodt, J. (2015). Self-evaluation and peer-feedback of medical students’ communication skills using a web-based video annotation system. Exploring content and specificity. *Patient Education and Counseling*, 98(3), 356-363.
50. Li, S., Yu, C. H., Wang, Y., & Babu, Y. (2019). Exploring adverse drug reactions of diabetes medicine using social media analytics and interactive visualizations. *International Journal of Information Management*, 48, 228-237.
51. Nereim, C., Bickham, D., & Rich, M. (2019). A primary care pediatrician's guide to assessing problematic interactive media use. *Current Opinion in Pediatrics*, 31(4), 435-441.