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Misinformation and disinformation in the age of AI for engineering: a scientometric analysis

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Abstract

Library professionals play a critical role in identifying and analyzing AI-generated misinformation and disinformation. This paper presents a scientometric analysis of publications retrieved from the Web of Science Core Collection, spanning from 2019 to the present, on the topics of misinformation/disinformation and AI within the field of engineering and computer science. Using CiteSpace, we conduct a co-citation analysis to identify key research trends and emerging fronts in this domain. Through CiteSpace, we analyze citation networks using key indicators such as betweenness centrality, citation burst detection, and Sigma to identify transformative works and emerging trends. This approach enables the detection of critical developments in areas such as AI-generated misinformation, detection methodologies, ethical implications, and educational responses within engineering contexts. The insights derived from this study offer valuable implications for engineering librarians and information specialists for research support and collection development purpose and can help inform future research directions. Librarians can apply a similar workflow in other research areas.

Background

The proliferation of misinformation and disinformation on the internet has been a concern, especially with the recent advances in AI technologies. Wu et al. [1] define misinformation as false or inaccurate information that is deliberately created and circulated, often without clear malicious purpose. Disinformation, while also incorrect, is differentiated by intent, as it is produced and disseminated specifically to mislead or deceive audiences. Misinformation and disinformation reinforce false beliefs. They create fear and mistrust, contribute to harmful outcomes like racism and hate crimes, and weaken both trust in knowledge and the foundations of democracy [2]. In healthcare, the spread of misinformation and disinformation can stop patients from seeking therapies for treatable conditions, for example.

Current Research on Misinformation and Disinformation

Due to the interdisciplinary nature of research in misinformation and disinformation, there have been several comprehensive literature reviews in this field. A study analyzed 1,261 publications between 2010 and 2021on misinformation, disinformation and fake news collected from Google Scholar. This study revealed that communication (30.1%) and computer science (18.6%) were the top contributors among all disciplines [3]. Disciplines such as psychology (8.4%), political science (7.4%), economics (7.4%) and health science (6.5%) were also well represented. They also reported “detection and/or characteristics” as the most prominent theme in computer science and computer science used computational methods the most among all disciplines. Similarly, a systematic review investigated 756 publications from Web of Science between 2014 and 2022 on misinformation and disinformation [4]. In their analysis, the top fields were health (48%), politics/democracy (21.4%), and scientific experiment (13.2%). The high frequency of misinformation and disinformation in health was attributed to the Covid-19 pandemic and the impact of this information on public health, especially in 2020, 2021 and 2022. This study also revealed that 67.9% of these fake news stories were presented as having a scientific bias, while 25.3% functioned as political propaganda.

AI or artificial intelligence plays a dual role in misinformation and disinformation. On one hand, AI makes it easier to create fake content and audios/videos (deepfakes) [5]. Meanwhile, AI can facilitate the spread of misinformation and disinformation through micro-targeting of audience and the employment of social bots [5]. On the other hand, AI tools have been used in content regulation, and the detection of fake social media accounts, autogenerated content and deepfakes. However, limitations in AI techniques have led to errors and can cause potential mistrust from users.

Use of Science Mapping Tools in the Study of Misinformation and Disinformation

Science mapping/visualization of bibliographic information is often used for data-driven information analysis. Bibliometric records are typically downloaded from Web of Science (WoS), Scopus, Google Scholar, Dimentions.ai, or Lens.org. Scientometric network types include co-citation, keyword co-occurrence, and bibliographic coupling [6]. Current literature demonstrated that CiteSpace, VOSviewer and HistCite were the top three most frequently used science mapping tools based on analysis of publications in WoS [7].

Science mapping tools have been implemented in the study of misinformation and disinformation. A systematic review in 2022 used VOSviewer to create keywords co-occurrence maps in the field of disinformation and multiliteracy [8]. They reported five groups of keywords: fake news/fact checking, disinformation/misinformation, critical thinking/deception/librarians, news media/credibility, and media literacy/scientific literacy. Another study used the R software to analyze 5,607 articles from WoS and Scopus published between 1971 to 2022 on misinformation/disinformation and libraries [9]. They identified top journals, important authors and most frequent keywords. "Artificial intelligence" was identified as a thematic cluster in this study. They also used the Multiple Correspondence Analysis technique in R to generate a thematic map and a thematic evolution graph to illustrate topics that increased or declined in popularity.

CiteSpace

In this study, we use CiteSpace as a tool for the visualization and analysis of data obtained from the Web of Science (WoS) Core Collection. CiteSpace is a well-recognized software for co-citation analysis and has been used in numerous studies to reveal the intellectual structure of a field, such as landmark/transformative publications, research fronts and evolution of research interests. Here we highlight some of the applications of CiteSpace in several studies from a variety of research areas.

In his pivotal article, Chen [10] implemented CiteSpace II to analyze two research fields: mass extinction (1981–2004) and terrorism (1990–2003). Nan et al. [11] collected articles related to ChatGPT from WoS and conducted a bibliometric analysis using CiteSpace. Their study visualized the research evolution surrounding ChatGPT through 2,465 articles collected from WoS. Sabe et al. [12], [13] have applied CiteSpace in mental health areas to identify research trends, co-citation journal networks and co-authorship networks.

Among other analytical techniques, visualization mapping in CiteSpace is designed for cluster and time-zone views. There are three structural and temporal indicators in CiteSpace used to identify significant publications in a field: the citation burst detection algorithm incorporates both intensity and duration time of citation surges to identify active research areas, the betweenness centrality metric is used to distinguish potential pivotal publications of paradigm shifts, and Sigma, which is defined as $(1+\text{centrality})^{\text{burstiness}}$, is a measurement of transformative publications [14]. Typically, a publication needs to have both high citation burst and betweenness centrality to demonstrate a high Sigma value. A more detailed definition of the terms used for data interpretation in CiteSpace can be found in the Appendix Table I.

Purpose

It is widely recognized that generative AI has increased misinformation and disinformation; as a result, the difficulty of evaluating information has become a significant concern. We focus our study on the publications of this topic in engineering and computer science. In this study, we analyze publications on AI and misinformation/disinformation in engineering and computer science collected from WoS Core Collection with CiteSpace. We attempt to reveal major research topics and research fronts in this field using structural and temporal measurements beyond traditional citation counts. These research topics and research fronts are analyzed beyond keywords, and significant publications in each topic are recognized to provide context. Previous work typically used keywords to define themes and information provided by these keywords are limited, especially when domain expertise is lacking [9]. To contribute to the knowledge of misinformation and disinformation research, we define the following research questions (RQs):

RQ1: What are the main research themes of the misinformation and disinformation research in computer science and engineering?

RQ2: What are the research fronts or active research areas in this field?

RQ3: How have research topics in this field evolved?

Insights from this study have important implications for engineering librarians/information specialists providing research support and can guide collection development based on the publication venues of significant publications. Librarians can apply a similar approach to analyze publications of their institutions or identify research directions in a field for grant proposals or policy documents.

Method

Bibliometric records were downloaded from WoS Core Collection on March 29, 2026, using the following search statement:
"artificial intelligence" OR AI
AND
misinformation OR disinformation OR "false information" OR "misleading information" OR "fake news" OR deepfake OR deepfakes

Publication time was limited from 2019 to 2026, and document types were limited to article, proceeding paper, review article, early access and book chapters. WoS categories were then limited to computer science and engineering. A total of 1,850 publications were identified. We extended our analysis to the citation articles of these 1,850 publications using the "citation reports" function in WoS, and a total of 12,648 publications were collected for analysis. Previous research suggested that cascading citation expansion can provide a more representative overview of a field and find topics that can be missing from traditional keywords-based literature search [15]. These 12,648 bibliometric records were downloaded as plain text files with the "full record and cited references" option in batches of 500 for software analysis. A detailed data collection and analysis flowchart can be found in Fig. 1. Duplicate removal in CiteSpace combines each year's publication into a single file and makes subsequent analysis much faster. In the current study, no duplicate records were removed since these publications are newer publications with DOIs assigned.

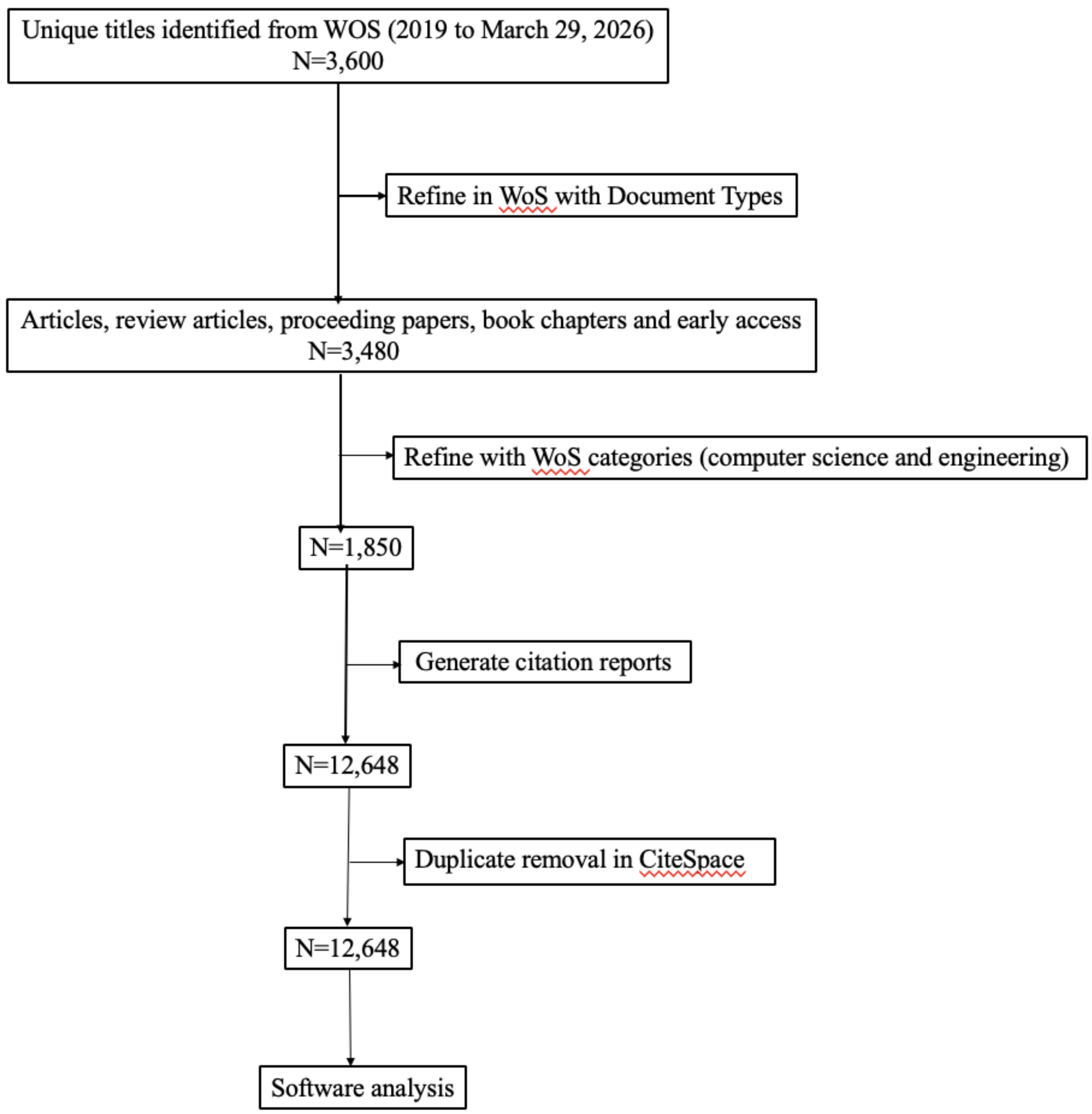

Fig. 1. Data collection and analysis flowchart

CiteSpace 6.4.R2 was used for data analysis. Citation look back year was set as –1, which means citations of all times were included. Time slicing was set as 1 year, which means each year's publication was analyzed as a unit. Link Retention Factor was set as 3, which decides the threshold of links to be kept. Articles selection criteria were set as $k = 25$, which decided how big the resulting network would be. K is a modified version of the *g*-index. A more detailed description of the procedure for librarians/information specialists can be found in [16].

RESULTS

Publication Output

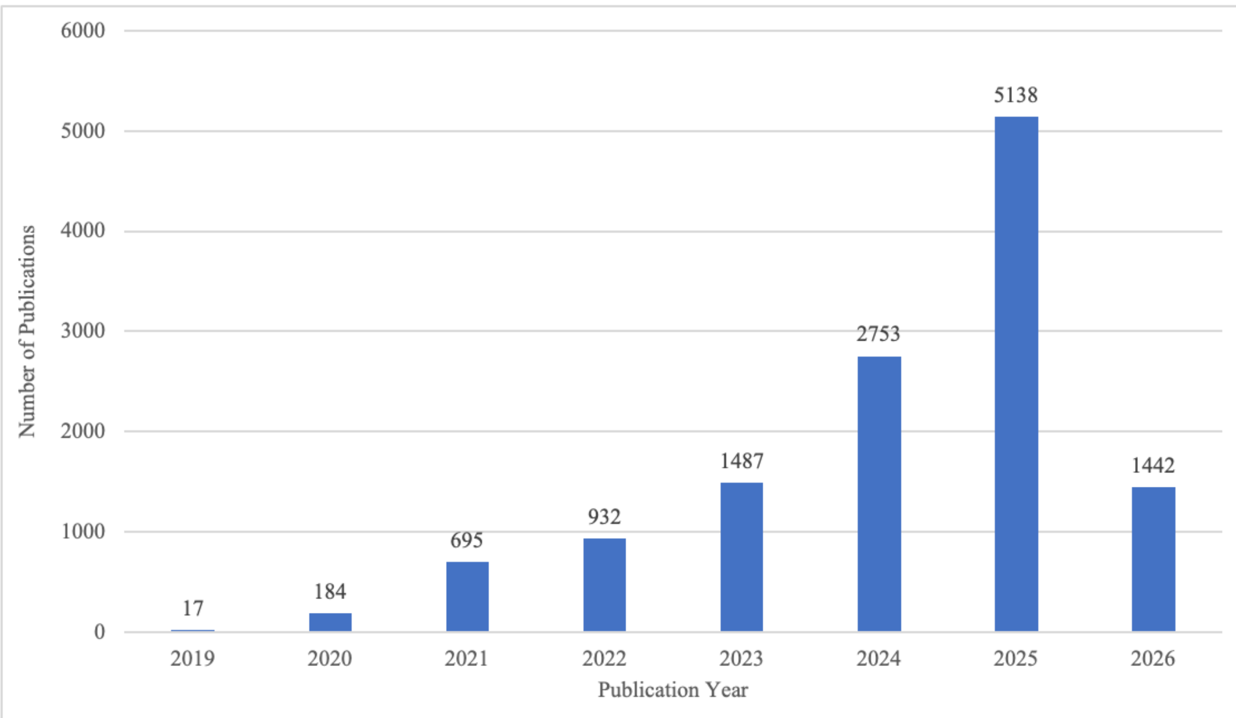

Fig. 2. Number of publications from 2019 to 2026 (partial)

Fig. 2 illustrates the number of publications each year from 2019 to 2026. It can be seen that the number of publications each year nearly doubled from the previous year from 2022 to 2025. The publication number of 2026 is not representative since the data was collected in March 2026.

Analysis of Clusters of Research Topics

As mentioned in the "CiteSpace" introduction section, three major indicators are examined in the composition of clusters #0 (fake news detection), #1 (deepfake detection), #2 (fake face images detection), and #6 (fake news detection with deep learning): citation burst detection, betweenness centrality, and Sigma. In contrast, for clusters #3 (Generative Adversarial Networks image synthesis and detection), and #8 (audio spoofing detection), the analysis focuses on betweenness centrality, since these clusters have no publications with citation bursts and high Sigma. Together, these approaches support the identification of active research areas, potential research interest shifts over time, and the recognition of transformative or bridging/gateway publications.

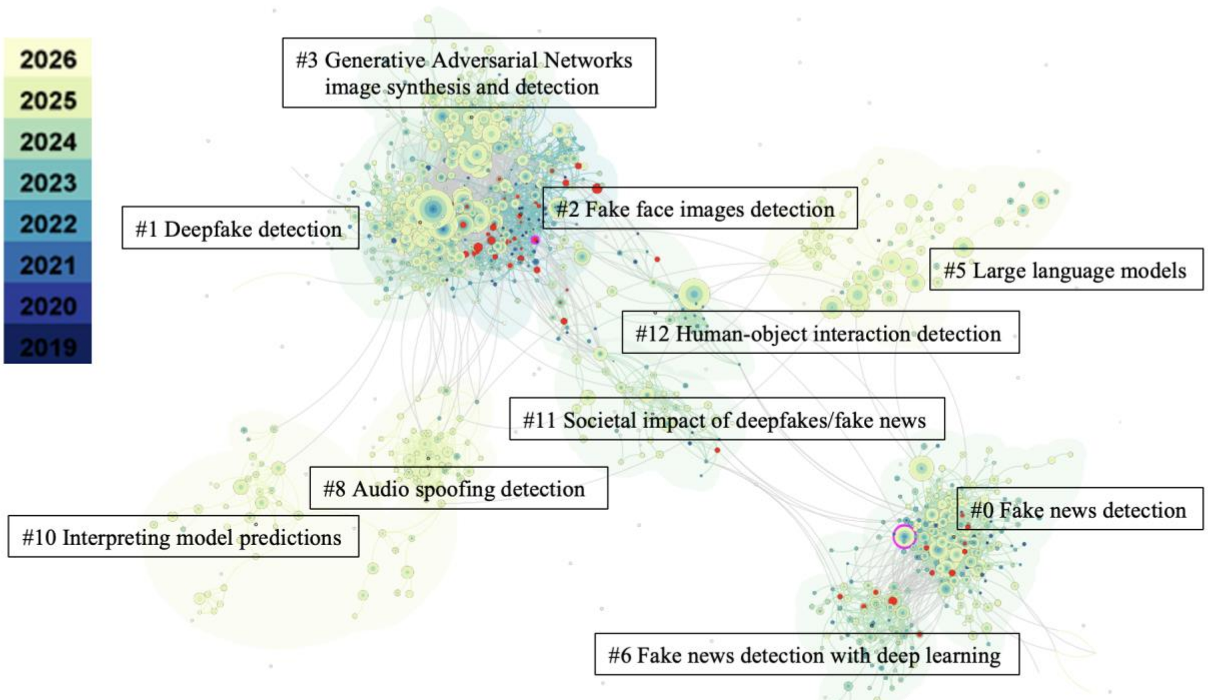

Fig. 3. Top ten largest co-citation clusters with tree-ring type nodes for AI and misinformation/disinformation research (2019-2026). The size of each node (article) is corresponding to the frequencies of co-citations. The color rings of each node indicate when the citations happened, as shown in the color bar on top left, from past (blueish) to present (yellowish). Nodes with a purple ring are references with high betweenness centrality. Nodes of red color are articles with citation bursts (minimum duration 3 years).

The largest ten clusters of co-citation analysis are demonstrated in Fig. 3 and Table I. A total of 1,686 nodes and 7,767 links were identified. Each node represents a cited reference, and a link indicates a co-citation occurrence. A total of 507,863 distinct references were analyzed, and 82 citation bursts were detected with a minimum three-year duration time, and 3.0 State Transition Cost α (which decides how difficult it is to move to a higher burst state).

Table I. Major clusters of co-citation analysis of AI and misinformation/disinformation publications from 2019 to 2026. Cluster numbers are not consecutive because only the largest connected component of the network is shown. Bold clusters are analyzed with significant publications in the following sections.

Cluster ID	Cluster Name	Size (Number of publications)	Silhouette	Mean (year)
0	**Fake news detection**	**186**	**0.896**	**2018**
1	**Deepfake detection**	**184**	**0.951**	**2020**
2	**Fake face images detection**	**182**	**0.726**	**2017**
3	**Generative Adversarial Networks image synthesis and detection**	**101**	**0.936**	**2019**
5	Large language models	69	0.992	2018
6	**Fake news detection with deep learning**	**68**	**0.948**	**2020**
8	**Audio spoofing detection**	**49**	**0.971**	**2020**
10	Interpreting model predictions	41	0.99	2018
11	Societal impact of fake news/deepfakes	40	0.99	2020
12	Human-object interaction detection	34	0.96	2018

Analysis of Top Four Largest Clusters

Table II. Cited references with the highest betweenness centrality in cluster #0 (fake news detection)

Betweenness Centrality	Network Citations	Author(s) and Year	Source	Article Title
0.18	343	Allcott and Gentzkow, 2017	Journal of Economic Perspectives	Social media and fake news in the 2016 Election
0.07	584	Devlin et al., 2019	Association for Computational Linguistics conference	BERT: Pre-training of deep bidirectional transformers for language understanding
0.03	137	Shu et al., 2019	ACM conference	Beyond news contents: the role of social context for fake news detection
0.03	316	Shu et al., 2017	ACM SIGKDD Explorations Newsletter	Fake news detection on social media: A data mining perspective

Table III. Cited references with the strongest citation bursts in cluster #0 (fake news detection)

Citation Bursts	Network Citations	Author(s) and Year	Source	Article Title
45.58	339	Sharma et al., 2019	ACM Transactions on Intelligent Systems and Technology	Combating fake news: A survey on identification and mitigation techniques
19.65	41	Wu et al., 2015	IEEE conference	False rumors detection on Sina Weibo by propagation structures
19.31	38	Ajao et al., 2018	ACM conference	Fake news identification on Twitter with hybrid CNN and RNN models
17.28	34	Qian et al., 2018	International Joint Conferences on Artificial Intelligence Organization conference	Neural user response generator: Fake news detection with collective user intelligence
17.25	36	Shu et al., 2018	IEEE conference	Understanding user profiles on social media for fake news detection
16.77	33	Yang et al., 2019	ACM conference	Unsupervised fake news detection on social media: A generative approach
16.77	33	Chen et al., 2018	Trends and Applications in Knowledge Discovery and Data Mining	Call attention to rumors: Deep attention based recurrent neural networks for early rumor detection

Table IV. Cited references with the highest Sigma in cluster #0 (fake news detection)

Sigma	Network Citations	Author(s) and Year	Source	Article Title
1.64	339	Sharma et al., 2019	ACM Transactions on Intelligent Systems and Technology	Combating fake news: A survey on identification and mitigation techniques
1.12	38	Ajao et al., 2018	ACM conference	Fake news identification on Twitter with hybrid CNN and RNN models
1.11	41	Wu et al., 2015	IEEE conference	False rumors detection on Sina Weibo by propagation structures
1.09	191	Wang, 2017	Association for Computational Linguistics conference	“Liar, Liar Pants on Fire”: A new benchmark dataset for fake news detection

Cluster #0 (fake news detection) is the largest cluster in the co-citation network, with 186 cited references and a mean publication time of 2018. Members of cluster #0 demonstrated high betweenness centrality, citation bursts and sigma values. Publications with highest betweenness centrality scores are shown in Table II. They discuss the spread of fake news on social media and the detection algorithms. The article with the highest centrality focuses on the consumption of fake news before the 2016 presidential election [17]. It is also one of the two publications with the highest betweenness centrality (0.18) in the entire dataset. Table III lists the top seven publication with the strongest citation surges. These articles detail various fake news detection techniques on social media, such as through user profiles or historical user response. The article with the highest citation burst is a survey on fake news detection methods and challenges on social media [18]. Four out of seven of these articles are the Institute of Electrical and Electronics Engineers (IEEE) or the Association for Computing Machinery (ACM) conference proceedings. When comparing articles with high betweenness centrality and those with strongest citation bursts, we can conclude that articles with high centrality tend to demonstrate higher in-network or local citations. On the other hand, most articles with strongest citation bursts do not show high citation counts. Since Sigma values measure both betweenness centrality and citation bursts, the top three articles with high Sigma values are the same three articles at the top of citation burst strength list, as shown in Table IV. The fourth article with high Sigma value is a free benchmarking dataset for automatic fake news detection, with a citation burst of 11.78 [19] (not shown in Table III). Some of these articles with high Sigma values received high citations, while some did not, which indicates that pivotal articles may not receive or have not had enough time to accumulate high citations.

Table V. Cited references with the highest betweenness centrality in cluster #1 (deepfake detection)

Betweenness Centrality	Network Citations	Author(s) and Year	Source	Article Title
0.07	383	Dang et al., 2020	IEEE conference	On the detection of digital face manipulation
0.05	333	Selvaraju et al., 2017	IEEE conference	Grad-CAM: Visual explanations from deep networks via gradient-based localization
0.05	67	Jia et al., 2018	Advances in Neural Information Processing Systems conference	Transfer learning from speaker verification to multispeaker text-to-speech synthesis
0.04	1180	Li et al., 2020	IEEE conference	Celeb-DF: A large-scale challenging dataset for deepfake forensics

Table VI. Cited references with the strongest citation bursts in cluster #1 (deepfake detection)

Citation Bursts	Network Citations	Author(s) and Year	Source	Article Title
73.33	733	Yang et al., 2019	IEEE conference	Exposing deep fakes using inconsistent head poses
53.62	425	Güera and Delp, 2018	IEEE conference	Deepfake video detection using recurrent neural networks
48.68	303	Zhou et al., 2017	IEEE conference	Two-stream neural networks for tampered face detection
46.98	455	Matern et al., 2019	IEEE workshop	Exploiting visual artifacts to expose deepfakes and face manipulations
32.20	236	Agarwal and Farid, 2019	IEEE workshop	Protecting world leaders against deep fakes
30.60	114	Cozzolino et al., 2017	ACM conference	Recasting residual-based local descriptors as convolutional neural networks: An application to image forgery detection

Table VII. Cited references with the highest Sigma in cluster #1 (deepfake detection)

Sigma	Network Citations	Author(s) and Year	Source	Article Title
1.30	455	Matern et al., 2019	IEEE workshop	Exploiting visual artifacts to expose deepfakes and face manipulations
1.23	733	Yang et al., 2019	IEEE conference	Exposing deep fakes using inconsistent head poses
1.12	425	Güera and Delp, 2018	IEEE conference	Deepfake video detection using recurrent neural networks
1.10	114	Cozzolino et al., 2017	ACM conference	Recasting residual-based local descriptors as convolutional neural networks: An application to image forgery detection

Cluster #1 (deepfake detection) is the second largest cluster in the network, with 184 cited reference and a mean publication year of 2020. Publications in cluster #1 also display high values in the three indicators for articles with structural and temporal significance. Table V lists the top four publications with the highest betweenness centrality. These four are all conference proceedings and discuss image manipulation detection and a system for text to speech synthesis. The article with the highest betweenness centrality is on the detection of forged face images [20]. Compared with publications in cluster #0 (fake news detection), publications in cluster #1 (deepfake detection) demonstrate stronger citation surges, as shown in Table VI. All the publications are conference proceedings on detection of tampered videos and facial images. The publication with the strongest citation burst is on the exposure of AI-generated face images or videos through 3D head poses [21]. As expected, all top publications with high Sigma values in this group are also on the citation burst list, as displayed in Table VII. In general, publications in cluster #1 (deepfake detection) demonstrate higher local citation counts compared with publications in cluster #0 (fake news detection). The publication with the highest network citation counts (1,180) for this entire dataset is in this group, which developed a large scale deepfake dataset for detection method evaluation [22]. It is also noteworthy that all publications analyzed in this group are conference proceedings, especially proceedings from the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR).

Table VIII. Cited references with the highest betweenness centrality in cluster #2 (fake face image detection)

Betweenness Centrality	Network Citations	Author(s) and Year	Source	Article Title
0.18	42	Nataraj et al., 2019	Society for Imaging Science and Technology conference	Detecting GAN generated fake images using co-occurrence matrices

Table IX. Cited references with the strongest citation bursts in cluster #2 (fake face image detection)

Citation Bursts	Network Citations	Author(s) and Year	Source	Article Title
56.24	93	Korshunov and Marcel, 2018	arXiv	DeepFakes: A new threat to face recognition? Assessment and detection
48.75	89	Dolhansky et al., 2019	arXiv	The Deepfake Detection Challenge (DFDC) preview dataset
41.73	87	Kingma et al., 2014	Neural Information Processing Systems conference	Semi-supervised learning with deep generative models
36.11	71	Dolhansky et al., 2020	arXiv	The DeepFake Detection Challenge (DFDC) dataset
27.70	36	Cozzolino et al., 2018	arXiv	ForensicTransfer: Weakly-supervised domain adaptation for forgery detection
27.58	91	Thies et al., 2016	IEEE conference	Face2Face: Real-time face capture and reenactment of RGB videos
23.49	49	Tariq et al., 2018	ACM conference	Detecting both machine and human created fake face images in the wild

Table X. Cited references with the highest Sigma in cluster #2 (fake face image detection)

Sigma	Network Citations	Author(s) and Year	Source	Article Title
28.45	42	Nataraj et al., 2019	Society for Imaging Science and Technology conference	Detecting GAN generated fake images using co-occurrence matrices
1.22	49	Tariq et al., 2018	ACM conference	Detecting both machine and human created fake face images in the wild
1.20	93	Korshunov and Marcel, 2018	arXiv	DeepFakes: A new threat to face recognition? Assessment and detection
1.16	89	Dolhansky et al., 2019	arXiv	The Deepfake Detection Challenge (DFDC) preview dataset
1.16	36	Cozzolino et al., 2018	arXiv	ForensicTransfer: Weakly-supervised domain adaptation for forgery detection

Cluster #2 (fake face image detection) is the third largest group in the merged network, with 182 publications and a mean publication time of 2017. There is only one publication with high betweenness centrality, as displayed in Table VIII. However, it is one of the two publications with the highest centrality value (0.18) in the entire dataset. This conference proceeding focuses on a novel approach of detecting Generative Adversarial Networks (GAN) generated fake images [23]. Publications of this cluster also demonstrate strong citation surges, as illustrated in Table IX. The citation burst publications are from either arXiv.org or conference proceedings. Although related to deepfake detection, they mainly focus on face recognition, such as face swapping in videos with GAN or face images generated by GAN. It is noteworthy that top two publications with the strongest citation bursts in this group are articles from arXiv.org directly, not self-archiving of conference proceedings on it. In contract to publications with high Sigma values in clusters #0 (fake news detection) and #1 (deepfake detection), publications with high Sigma values in cluster #2 (fake face image detection) include those on both the betweenness centrality and citation burst lists, as shown in Table X. This can be explained by the appearance of one of the two publication with the highest betweenness centrality in the whole dataset in this group. The *S* score of cluster #2 (fake face image detection) is the lowest (0.726) among the top ten largest clusters analyzed in this study (see Table I). Although still indicating a quality clustering, this relatively lower *S* (silhouette) score also suggests that cluster #2 is less isolated than other clusters identified in this study, since fake face image detection (cluster #2) is closely related to deepfake detection (cluster #1).

Table XI. Cited references with the highest betweenness centrality in cluster #3 (Generative Adversarial Networks (GAN) image synthesis and detection)

Betweenness Centrality	Network Citations	Author(s) and Year	Source	Article Title
0.05	189	Lin et al., 2014	European Conference on Computer Vision	Microsoft COCO: Common objects in context
0.04	335	Choi et al., 2018	IEEE conference	StarGAN: unified Generative Adversarial Networks for multi-domain image-to-image translation
0.02	585	Karras et al., 2019	IEEE conference	A style-based generator architecture for Generative Adversarial Networks
0.02	413	Wang et al., 2020	IEEE conference	CNN-generated images are surprisingly easy to spot... for now
0.02	182	Zhang et al., 2019	IEEE workshop	Detecting and simulating artifacts in GAN fake images

Cluster #3 (Generative Adversarial Networks (GAN) image synthesis and detection) has 101 members with a mean publication time of 2019. Five publications in this group demonstrate higher betweenness centrality, as displayed in Table XI. They focus on GAN for image generation and detection of such fake images. Three out of the five publication with high centrality are from the Computer Vision Foundation conference of IEEE, indicating an important publication venue for this field. However, no publications display high citation surges and hence high Sigma values. It can also be seen that cluster #3 is closely connected with cluster #1 (deepfake detection) and #2 (fake face image detection) in the visualization map (Fig. 3).

Insights into Research Fronts

Based on mean year of major clusters, cluster #1 (deep fake detection, mean year 2020), #6 (fake news detection with deep learning, mean year 2020) and #8 (audio spoofing detection, mean year 2020) are identified as research fronts since these clusters are newest and demonstrate research interests in the latest years. Cluster #1 (deep fake detection) has been discussed in the previous section as one of the top four largest clusters. We analyze clusters #6 and #8 in the following section.

Table XII. Cited references with the highest betweenness centrality in cluster #6 (fake news detection with deep learning)

Betweenness Centrality	Network Citations	Author(s) and Year	Source	Article Title
0.01	228	Kaliyar et al., 2020	Cognitive Systems Research	FNDNet – A deep convolutional neural network for fake news detection
0.01	37	Bahad et al., 2020	Procedia Computer Science	Fake news detection using Bi-directional LSTM-Recurrent Neural Network
0.01	177	Kaliyar et al., 2021	Multimedia Tools and Applications	FakeBERT: Fake news detection in social media with a BERT-based deep learning approach
0.01	55	Mridha et al., 2021	IEE Access	A comprehensive review on fake news detection with deep learning
0.01	78	Wang, 2017	arXiv	"Liar, liar pants on fire": a new benchmark dataset for fake news detection

Table XIII. Cited references with the strongest citation bursts in cluster #6 (fake news detection with deep learning)

Citation Bursts	Network Citations	Author(s) and Year	Source	Article Title
14.74	228	Kaliyar et al., 2020	Cognitive Systems Research	FNDNet – A deep convolutional neural network for fake news detection
10.12	61	Reis et al., 2019	IEEE Intelligent Systems	Supervised learning for fake news detection
9.00	48	Umer et al., 2020	IEEE Access	Fake news stance detection using deep learning architecture (CNN-LSTM)
7.27	103	Ozbay and Alatas, 2020	Physica A: Statistical Mechanics and its Applications	Fake news detection within online social media using supervised artificial intelligence algorithms
5.70	37	Bahad et al., 2020	Procedia Computer Science	Fake news detection using Bi-directional LSTM-Recurrent Neural Network

Table XIV. Cited references with the highest Sigma in cluster #6 (fake news detection with deep learning)

Sigma	Network Citations	Author(s) and Year	Source	Article Title
1.08	228	Kaliyar et al., 2020	Cognitive Systems Research	FNDNet – A deep convolutional neural network for fake news detection
1.04	37	Bahad et al., 2020	Procedia Computer Science	Fake News Detection using Bi-directional LSTM-Recurrent Neural Network
1.01	103	Ozbay and Alatas, 2020	Physica A: Statistical Mechanics and its Applications	Fake news detection within online social media using supervised artificial intelligence algorithms

Cluster #6 (fake news detection with deep learning) has 68 cited references and a mean publication year of 2020. Compared with the top three largest clusters, this cluster is smaller and its members demonstrate lower betweenness centrality and citation burst strength. The five publications with top betweenness centrality are shown in Table XII, and the five publications with strongest citation bursts are displayed in Table XIII. Two publications are on both lists, and they are also on the publication list with high Sigma values, which are illustrated in Table XIV [24] [25]. Members in this group are on fake news detection with deep learning such as Bidirectional Encoder Representations for Transformers (BERT), which go beyond typical techniques such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Cluster #6 (fake news detection with deep learning) appears to be a recent development of cluster #0 (fake news detection) with new transformer models such as the deep convolutional neural network, BERT, or Long Short-Term Memory (LSTM) neural network. These two clusters are also very close to each other in the visualization map (see Fig. 3). We would like to point out that one of the publications on the centrality list is from arXiv [26], which is in fact the same article on the Sigma value publication list for cluster #0 (fake news detection) that was published in an Association for Computational Linguistics conference proceeding [19]. In CiteSpace, duplicates are removed if they match in the first ten letters of the source [27]. Since these two records are from different sources, these two nodes could not be merged in the network or get one of them removed in the duplicate removal procedure. This issue could be a limitation of our study. Meanwhile, this citing behavior (to cite the original conference proceedings or the post-prints on arXiv) can be further researched.

Table XV. Cited references with the highest betweenness centrality in cluster #8 (audio spoofing/deepfake detection)

Betweenness Centrality	Network Citations	Author(s) and Year	Source	Article Title
0.02	122	Wang et al., 2020	Computer Speech and Language	ASVspoof 2019: A large-scale public database of synthesized, converted and replayed speech

0.01	78	Chintha et al., 2020	IEEE Journal of Selected Topics in Signal Processing	Recurrent convolutional structures for audio spoof and video deepfake detection
0.01	13	Chen et al., 2020	International Speech Communication Association conference	Generalization of audio deepfake detection
0.01	42	Ricardo and Tzerpos, 2019	IEEE conference	FoR: A dataset for synthetic speech detection
0.01	43	van den Oord, et al., 2016	arXiv	WaveNet: A generative model for raw audio
0.01	51	Zhang et al., 2021	IEEE Signal Processing Letters	One-class learning towards synthetic voice spoofing detection

Cluster #8 (audio spoofing/deepfake detection) is smaller than previous clusters discussed with 49 cited references and a mean publication time of 2020. This cluster has six publications with high betweenness centrality, as displayed in Table XV. The publication with the highest centrality is a public database of synthesized speech [28]. There are no publications with citation bursts and high Sigma values in this group.

Research Theme Shift Based on Cluster Dependencies

We further analyze the evolvement of research interests in this field with cluster dependencies as shown in Fig. 4.

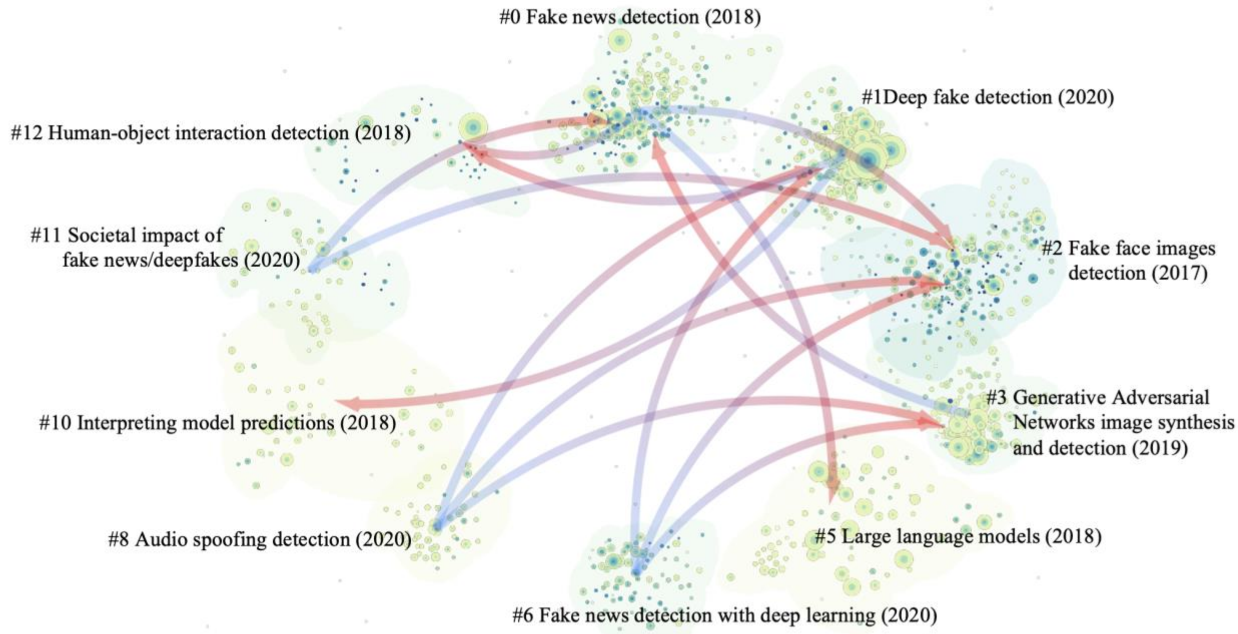

Fig. 4 Cluster dependencies of major co-citation clusters for AI and misinformation/disinformation research in engineering (2019-2026). Top 50% dependency paths are illustrated, and clusters are displayed with a circular map.

In cluster dependencies analysis, cluster A → cluster B indicates that cluster A cites articles and draws information from cluster B. We can see how relatively new clusters have been developed: Cluster #6 (fake news detection with deep learning) draws information from clusters #1 (deep fake detection), #2 (fake face image detection), and #3 (GAN image synthesis and detection). Cluster #8 (audio spoofing detection) was also developed from the same three previous clusters (clusters1, 2 and 3). Meanwhile, cluster #11 obtains valuable information from previous works in clusters #0 (fake news detection) and #2 (fake face images detection).

Discussion

This study analyzed publications on AI and misinformation/disinformation in the past seven years, which is a relatively short time for scientometric studies. In summary, clusters #3 (Generative Adversarial Networks image synthesis and detection) and #8 (audio spoof/deepfakes detection) were examined through cited references with the highest betweenness centrality, highlighting publications that function as intellectual bridges across research areas. In contrast, clusters #0 (fake news detection), #1 (deepfake detection), #2 (fake face images detection), and #6 (fake news detection with deep learning) were analyzed using a combination of cited references with the highest betweenness centrality, the strongest citation bursts, and the highest Sigma, allowing for the identification of both structurally influential and rapidly emerging works. With the tremendous development in this field, our study provides valuable insights into the overview of research progress in this field. Based on the number of publications with citation bursts in each cluster, we can conclude that there have been more research hotspots in cluster #0 (fake news detection), cluster #1 (deepfake detection), and cluster #2 (fake face images detection), with cluster #1 (deepfake detection) demonstrating the strongest citation surges. However, other areas such as cluster #10 (interpreting model predictions) and cluster #11 (societal impact of fake news/deepfakes), have also been important research areas with questions raised such as how to explain artificial intelligence, and the challenges deepfakes created for trust and democracy.

As far as research fronts are concerned, we used the mean year of a cluster as indicators, that is, the newest clusters represent latest research interests. However, since the time frame of this study is relatively short, the mean year of major clusters are very close to each other. It is reasonable to assume that all these major clusters/research topics identified through co-citation analysis can still be active research areas.

Although scientometric analyses involve large and complex datasets, they are particularly well suited to capturing the rapid evolution of AI-related research. By systematically examining publication patterns, co-citation networks, and cluster dependencies, this study uncovers intellectual linkages and research fronts that are not easily identifiable through traditional literature reviews. The use of CiteSpace enhances analytical rigor by providing visualizations and quantitative metrics that support objective data-driven interpretation. As a result, this method not only reduces bias but also offers evidence-based insights for research evaluation, policy development, and future directions in the study of AI related misinformation and disinformation.

Conclusion and Limitations

In conclusion, scientometric studies rely on statistical analyses of citation patterns within a given field of study. Their primary aim is to reveal the intellectual structure of a discipline through content analysis, including the identification of thematic clusters. In this study, we employ a scientometric approach to examine the emerging body of literature on generative AI-driven misinformation and disinformation within the fields of engineering and computer science. Using CiteSpace, we mapped the knowledge domain by identifying key clusters, influential publications, and the relationships among core research themes. We collected a total of 12,648 bibliometric records from WoS Core Collection and conducted co-citation analysis with CiteSpace. We analyzed the four largest clusters for major research topics and the two clusters with most recent mean years for research fronts. In each cluster, we identified significant publications using the betweenness centrality, citation bursts and Sigma. We further demonstrated the evolvement of research fronts through cluster dependencies. Findings in this study provide valuable information for librarians/information specialists providing research support in this area and can guide future research directions. Librarians can apply this research approach in the fields they are interested in.

Our study has its limitations. Although one purpose of scientometric study is to reveal the intellectual structure of a domain without subject expertise, we could have conducted a survey to gather faculty feedback on the themes, research fronts, and transformative publications we identified in this field. We collected our data from WoS Core Collections, which is a very selective database and may not represent all significant research in this field. Various biases associated with citing behavior are other limitations in a scientometric analysis. Meanwhile, scientometrics studies the quantitative impact of literature. There are qualitative scholarly or societal impact that cannot be measured by citations.

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Appendix

Table I. Definitions of major terms used in data interpretation

Term	**Definition**
Co-citation	Two articles are considered co-cited if they are cited by the same subsequent article. In CiteSpace, co-cited references form the knowledge base of a domain, and citing articles constitute the research fronts of a field.
Silhouette	Silhouett score measures how homogenous a cluster is and how consistent the clustering is. Its value is [-1,1]. A value above 0.7 suggests a credible clustering, and a value of 1 validates a perfect clustering.
Citation burst	Surge of citations in a short period of time, which indicates active research areas that receive attentions from researchers. Both strength and duration of a burst are measured. The number of citation bursts can

	be adjusted with parameters such as duration time, State Transition cost α, and growth rate γ . Nodes with citation bursts are marked as red dots in visualization.
Betweenness centrality	It is calculated for each node in the co-citation network. It is the possibility of the shortest path for any pair of nodes in the network to go through a specific node. Its value is [0,1]. It measures how potential a paper can be transformative. A node with high betweenness centrality typically connects/bridges distinct clusters. It is marked with a purple ring in visualization.
Sigma	Combines both burstness and betweenness centrality. Sigma = (1+centrality)^burstness A paper will have a high Sigma value if it has strong values in both burstness and betweenness centrality.