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Research article

COVID-19 and diabetes research: Where are we now and what does the future hold? A bibliometric visualization analysis

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A R T I C L E I N F O

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A B S T R A C T

Background & objective: The extensive spread of Coronavirus disease 2019 (COVID-19) worldwide has caused a dramatic negative impact on many individuals' health. This study aims to systematically and comprehensively analyze the current status and possible future directions of diabetes mellitus (DM) and COVID-19 research.
Methods: We obtained publications about COVID-19 and DM from the Web of Science Core Collection (WoSCC) using the search terms "COVID-19″ and similar terms combined with "DM" and similar terms, with a date range of January 2020 to May 2024. And we used CiteSpace V 6.3. R2 to perform the bibliometric visualization analysis.
Results: The search enrolled 6266 publications. The USA is a country with the most publications; Harvard University was the most productive institution in this field. The highest-ranked journal was the PLOS ONE, and the most cited journal was Lancet. The 20 most cited journals have all been cited 28754 times, accounting for 28 % of the total cites; the range of those journals was 790–3197. Publications on COVID-19 and DM research exhibited a distinct trajectory, shifting from an initial emphasis on understanding the impact of diabetes on COVID-19 infection and its associated pathophysiological mechanisms to a focus on analyzing the differential responses of diverse patient populations. Subsequently, research has progressed to examine the effects of medications and vaccines, as well as the long-term consequences of COVID-19 in diabetic individuals. Throughout this research endeavor, the exploration of diverse therapeutic interventions, their efficacy, and ultimate outcomes have consistently remained a paramount focus. And " metabolic syndrome," " long COVID," and " gestational diabetes" are still likely to be the hotspots and frontiers of research in the future.
Conclusions: This bibliometric analysis related to DM in COVID-19 illuminates the current research situation and developmental trends, supporting researchers in the exploration of prospective directions for research.

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List of abbreviations

COVID-19	Corona Virus Disease 2019
SARS-CoV-2	Severe Acute Respiratory Syndrome-Coronavirus-2
DM	Diabetes Mellitus
T2DM	Type 2 Diabetes Mellitus
WHO	World Health Organization
ACE2	Angiotensin-converting Enzyme 2
ICS	Inhaled Corticosteroids
GDM	Gestational diabetes mellitus
WoSCC	Web of Science Core Collection
WoS	Web of Science
JCR	Journal Citation Reports
JIF	Journal impact factors

1. Introduction

Coronavirus disease 2019 (COVID-19) is an acute respiratory epidemic resulting from severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2). It continues to spread out of control globally, with 775.62 million people infected worldwide as of June 2024, resulting in 7.05 million deaths[https://covid19.who.int/]. The ongoing mutations of the Omicron variant continue to drive an increasing number of COVID-19 patients. Since the outbreak of the COVID-19 pandemic, numerous studies have shown that crowds with comorbidities are at higher risk of developing severe COVID-19 complications. According to the US Centers for Disease Control and Prevention, diabetes mellitus (DM) is the most common comorbidity of COVID-19 [13]. As chronic metabolic disease, DM is characterized by insulin and glucose metabolism disturbances. The World Health Organization (WHO) estimates that DM affects 8.5 % of those over 18 years and will be the seventh cause of death worldwide by 2030 [27]. Epidemiological data suggest that type 2 diabetes mellitus (T2DM) accounts for approximately 90 % of all DM cases [12]. Several studies have shown the bidirectional interaction between DM and COVID-19 [1,14]. DM has now been shown to be one of the major risk factors for severe COVID-19 pneumonia, and COVID-19 pneumonia is also an influencing factor for DM [49].

Recently, researchers have focused on the complex relationship between COVID-19 and DM. The number of publications deciphering the complex interaction mechanisms between DM and COVID-19 has increased significantly. The explosion of publications, however, can leave researchers bogged down in a flood of information and lacking a comprehensive and holistic understanding of the domain. Thus, a comprehensive and systematic bibliometric analysis of the literature published on COVID-19 and DM research during this period is essential. Bibliometric analysis serves as a valuable tool that employs statistical and mathematical methods to quantitatively analyze and describe published research distribution patterns. This approach effectively assesses the impact, trends, and future research frontiers within a specific field [16,18,38]. The increasing availability of both basic and clinical research data, coupled with the increasing accessibility of free bibliometric tools in recent years, has led to a surge in interest in biomedical bibliometric analysis and data visualization.

Bibliometric methods have been conducted to demonstrate the research hotpots and trends of COVID-19 and DM. Wen et al. and Li et al. utilized CiteSpace software to conduct separate visualization analyses of COVID-19 imaging literature and COVID-19 related DM literature, respectively, with the aim of exploring their respective research landscapes, hotspots, overall trends, and predicting future research directions [55,75]. Vishwanathan's study visualized research trends in COVID-19 and DM by analyzing the top 100 cited articles，revealing the institutions and countries that have made the most significant contributions to this field [73]. Another study on COVID-19 and DM, Lin, X. et al. using bibliometric analysis, identified the dominant themes and keywords in the field [56]. However, COVID-19 and DM are not thoroughly examined, nor have quarterly bibliometric assessments been performed. In this study, we employed bibliometric analysis to identify COVID-19 and DM-related publications and generate a knowledge map, and assess emerging trends, hot spots and future research priorities.

2. Methodology

2.1. Study design

This study was a retrospective cross-sectional study regarding COVID-19 and DM.

2.2. Data acquisition and search strategy

To ensure the accuracy and comprehensiveness of data retrieval, citation data for this study were sourced from the Web of Science Core Collection (WoSCC), specifically including the following sub-databases: Science Citation Index Expanded (coverage years: 2014 to present), Current Chemical Reactions (coverage years: 1985 to present) and Index Chemicus (coverage years: 1993 to present)

[45,59]. A number of factors influenced this decision. First of all, WoSCC is the oldest and most extensively utilized citation

database globally, encompassing a broad range of academic disciplines [8]. It is distinguished by its high-quality metadata, precise citation data, advanced search and analytical tools, and a wide network of collaborative partnerships. These attributes provide a robust and accurate foundation for bibliometric research, establishing WoSCC as a premier platform for comprehensive and detailed research evaluation [33,53,62]. And the data obtained from WoSCC have a distinct advantage over other databases such as Scopus, PubMed: they can be analyzed directly using bibliometric software without the need for format conversion [60]. Several researchers have referred to WoSCC as the best database for bibliometric analysis [31]. As a result of these factors, WoSCC is the best choice for our data retrieval requirements.

We consulted published bibliometric studies on COVID-19 and DM to ensure that our literature collection is comprehensive and accurate [29,55,56]. Also, we utilized a comprehensive set of relevant keywords associated with COVID-19 and DM. The initial set of search terms was determined by a pilot run followed by subsequent adjustments. We then solicited expert review of our search strategy from leading researchers in the field, incorporating their feedback into our methodology. The final search strategy employed was as follows: TS= (SARS-COV-2 OR COVID-19 OR (coronavirus NEAR/1 2019) OR (coronavirus NEAR/1 2) OR (ncov NEAR/1 2019)) AND TS= ("diabet*" OR T2DM OR T2D OR T1DM OR T1D OR "DM type" OR NIDDM OR IDDM OR "DM2" OR "DM1") AND Language = English AND Documents = Article. The time scan covered 18 quarters, from January 2020 to May 2024. To avoid potential bias caused by daily updates, data retrieval was performed on June 1, 2024.

Initially, 10068 articles were retrieved. Following this, 178 non-English articles and 3198 publications classified as reviews, conference proceedings, news reports, corrections, and books were excluded. This resulted in a refined dataset of 6692 articles. A manual screening process was followed to eliminate publications solely related to COVID-19 or DM that did not meet the specific research requirements. This final stage resulted in the inclusion of 6266 research articles in this study. The 6266 retrieved research articles were downloaded as 'plain text files' with 'Full Records and Citations', categorized by quarter, and then statistically analyzed using CiteSpace V 6.2.R2 (Drexel University, USA). Journal impact factors (JIF) and subject categories were obtained from the Journal Citation Report 2023 (JCR, http://clarivate.com/Products/Web of Science). The flowchart of the search strategy and selection procedures is shown in Fig. 1.

2.3. Bibliometric analysis

CiteSpace, developed by Professor Chaomei Chen, is a bibliometric software that utilizes time-slice technology to establish evolving network models over time. It innovatively combines diachronic citation analysis and synchronic co-citation analysis to construct a theoretical model that maps from "knowledge bases" to "research fronts." [26] These individual networks are then integrated to form a comprehensive network, enabling a systematic investigation of relevant literature [18,24,71]. It has been widely used to explore research trends and patterns across numerous theoretical fields [39,44,60]. To gain a comprehensive understanding of the evolving research landscape in COVID-19 and DM, we utilized CiteSpace to construct visualized knowledge maps encompassing journals,

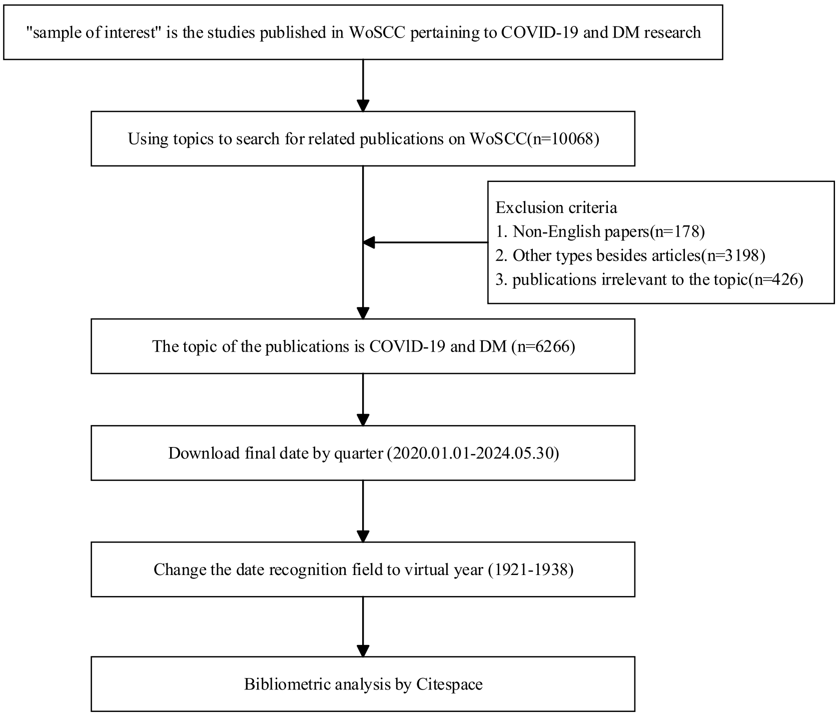

Fig. 1. The flowchart illustrating the search strategy and selection process.

country co-authorship, institution co-authorship, author co-authorship, co-cited references, and keyword co-occurrence quarterly. Furthermore, we conducted a cluster analysis of co-cited references and keywords, as well as a dual-map overlay analysis technique. These analyses contribute to visualizing foundational knowledge, research hotspots, overall trends, and potential future directions in the research field of COVID-19 and DM. CiteSpace extracts noun phrases using three specific indicators: latent semantic indexing, log-likelihood ratio, and mutual information. The log-likelihood ratio has been demonstrated in previous research as the most effective method for extracting labels for cluster analysis [52]. Thus, the log-likelihood ratio algorithm was used in this study to extract noun phrases. Microsoft Excel was used to count the number of annual publications and citations.

In the knowledge map, each node represents the object of analysis, such as countries, institutions, keywords, or co-cited references. The size of the ring around each node reflects the number of publications associated with that node [17]. The color of the ring denotes the corresponding virtual year [18,24]. The line between the nodes represents a cooperative relationship; the thicker the line, the more cooperative the relationship. CiteSpace's "betweenness centrality" function, based on the "tree hole" theory, identifies and evaluates influential documents within a field [2]. Nodes with a centrality score above 0.1 are considered to have high centrality, and the publications associated with them are often considered to play a pivotal role in driving the overall development of the academic field, deemed intellectual turning points [10,20,22]. Additionally, CiteSpace has a "burstness detection" feature that can foreshadow emerging academic trends, anticipate future research frontiers, and highlight potential topicality within a discipline. Burst strength refers to the sudden increase in citation frequency of a specific keywords or themes within a defined time period, reflecting its prominence and topical relevance during that period. In-depth analysis of nodes exhibiting highest citation bursts reveals nascent academic trends and research hotspots [32]. The knowledge maps, nodes exhibiting burst characteristics are filled with red color in the corresponding burst year to distinguish them. CiteSpace's cluster view provides a visual representation of the knowledge network structure characterizing different research areas, highlighting key nodes and critical connections [15]. During cluster analysis, CiteSpace employs two metrics—modularity (Q value) and average silhouette (S value) to assess the network structure and clarity of the clusters [23]. The Q value, typically ranging from 0 to 1, signifies a significant cluster structure when exceeding 0.3. The S value, on the other hand, evaluates the effectiveness and rationale of clustering [19]. A high S value, reaching 0.7, indicates effective and convincing clusters, while values above 0.5 are reasonable [19]. These metrics contribute to evaluating the quality and effectiveness of the generated maps.

In this study, we utilized the number of published articles as a quantitative metric to assess research productivity across countries, sources, institutions, and authors. Furthermore, we conducted a comprehensive evaluation of the published literature using multiple qualitative indicators, including the number of publications, total citations, average citations per publication, and the H-index. The H-index, a widely recognized metric, represents the number of articles (H) that have received at least H citations [40]. A higher h-index for an individual indicates greater influence of their publications. These data were obtained partly directly from the WoSCC and partly through analysis using CiteSpace software. By integrating the visualization maps with these quantitative and qualitative indicators, this research aims to comprehensively assess the current state of research on COVID-19 and DM, identify emerging trends, and predict future research frontiers.

3. Results

3.1. Date of publication analysis

A total of 6266 papers were examined in this study, accumulating 192,553 citations, resulting in an average of 30.7 citations per publication and an H-index of 154. The first quarter of 2020 witnessed the lowest number of publications related to COVID-19 and DM with only 60 articles published. However, the first quarter of 2020 also saw the highest average number of citations per publication. From the second quarter of 2020 onwards, there was a significant increase in the number of publications in this field, accompanied by a noticeable decline in the average number of citations per publication. The first peak in publication count was observed in the first quarter of 2021, followed by a second peak in the first quarter of 2022. The number of publications in subsequent quarters remained

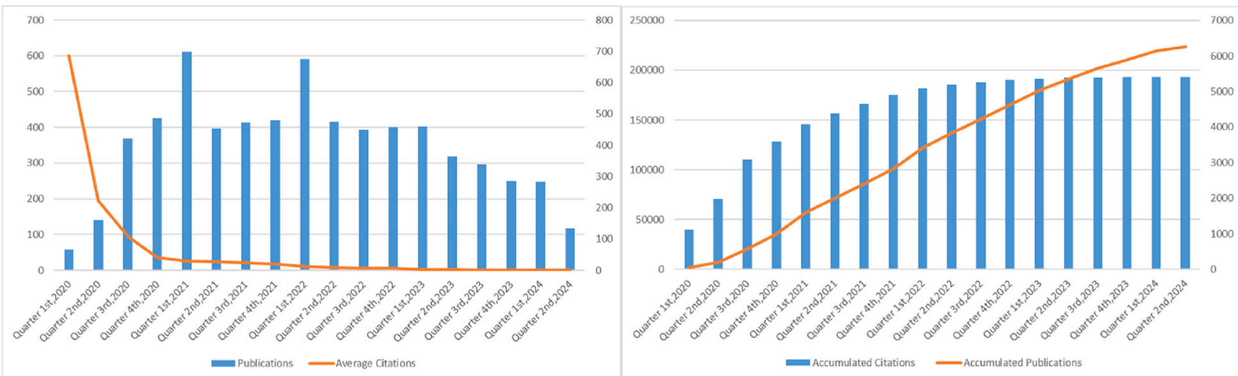

Fig. 2. Trends in the growth of publications and the number of citations. Left Y-axis: number of publications; Right Y-axis: number of citations.

relatively stable from 2021 to the first quarter of 2023. Since the second quarter of 2023, there has been a decreasing trend in the number of publications related to COVID-19 and DM. Fig. 2 exhibits the quarterly distribution of publications in this area and the number of citations to those publications for the past 18 quarters.

3.2. Analysis of country, institutional distribution and funding agencies

Collaborative studies on COVID-19 and DM have been performed in 157 countries and regions. Details of the top 10 prolific countries are listed in Table 1. The USA (1707, 27.24 %), China (704, 11.20 %), Italy (550, 8.78 %), the UK (540, 8.61 %), and India (397, 6.34 %) are the top five countries in terms of the number of articles published in this area, with these countries accounting for more than half of the total reports. In terms of publication quality, China exhibited the highest average number of citations per publication at 116.1, while the USA achieved the highest H-index, reaching 106. Only England (0.12) has centrality greater than 0.1, indicating that the country plays a crucial role in pushing the field forward.

The top 10 most active funding agencies are listed in Table 2. The United States Department of Health and Human Services and the National Institutes of Health are the leading contributors, with 472 and 450 articles, respectively. These articles have received 21,694 and 20,730 citations, resulted in an average of 46 and 46.07 citations per article. They also have H-indexes of 67 and 64 respectively. The National Natural Science Foundation of China follows with 195 articles, 9508 citations, an average of 48.76 citations per article, and an H-index of 40. These funding agencies contributions have played a crucial role in advancing the understanding and management of COVID-19 and DM.

The top 10 institutions regarding the number of publications in this field are shown in Table 3. Harvard University (213, 3.40 %) was the most active institution, followed by University College London (182, 2.90 %), the University of California System (172, 2.74 %), the Institut National de la Santé et de la Recherche Médicale (138, 2.20 %), and the University of Paris (125, 1.99 %). While Huazhong University of Science and Technology does not have the greatest number of publications, it exhibits the highest average number of citations (297.64) and the highest H-index (35). Among the top ten institutions based on publication count, Harvard University and Oxford University possess betweenness centrality of 0.13 and 0.11, respectively, exceeding the threshold of 0.1.

3.3. Analysis of author distribution

The cooperative analysis of authors shows that "Khunti, K″ was the most productive author from the University of Leicester, who contributed 36 articles, and also achieved the highest citations and H-index among authors. Holl, R W" (17) and "Cariou, B" (14) follow closely. In addition, an analysis of co-cited authors shows that of the top 10 most cited authors, the top 3 cited authors are all from China, namely "Zhou F" (1025), "Guan W" (936) and "Huang CL" (718). The top 10 authors and Co-Cited authors on COVID-19 and DM research are listed in Table 4.

3.4. Analysis of cited journals

A total of 1285 journals have published articles in this field. Among the top 20 journals, PLOS ONE ranks first with 252 articles in the previous 18 quarters. Among the co-cited journals, all journals have been cited 102693 times. The 20 most cited journals have all been cited 28754 times, accounting for 28 % of the total citations; the range of those journals was 790–3197. Lancet was the most cited journal (3197 times), followed by New England Journal of Medicine (3004 times) and JAMA-Journal of the American Medical Association (2827 times). Details of information on co-cited journals, such as JIF, JIF quartile, centrality and total citations, are provided in Table 5.

In the dual-map overlay analysis of journals, the left side represents the subject categories of citing journals, reflecting areas of active interest or emerging fields, while the right side depicts the subject categories of cited journals, forming a reference knowledge base. Each colored circle represents a specific journal. In the left-hand map, the longer the horizontal axis of an ellipse, the greater the number of publications in the corresponding journal. The longer the vertical axis, the greater the number of authors publishing in that journal [52]. The curves represent citation relationships between journals, with various colors indicating citation links between

Table 1
The top 10 prolific countries/regions.

Rank	Country /Region	Counts	% Of 6266	Citations	Average Citations	H-index	Centrality
1	USA	1707	27.24 %	56065	32.84	106	0.02
2	China	704	11.20 %	71244	101.2	71	0.03
3	Italy	550	8.78 %	16659	30.29	63	0.06
4	England	540	8.61 %	24221	44.85	64	0.12
5	India	397	6.34 %	7658	19.29	38	0.03
6	Spain	300	4.79 %	10739	35.8	46	0.03
7	Brazil	276	4.40 %	6540	23.7	34	0.02
8	France	243	3.88 %	9641	39.67	44	0.02
9	Germany	243	3.88 %	7871	32.39	38	0.05
10	Saudi Arabia	231	3.69 %	2525	10.93	25	0.02

Table 2
The top 10 active funding agencies.

Funding agencies	Articles	Citations	Average citations	H-Index
United States Department of Health and Human Services	472	21,694	46	67
National Institutes of Health	450	20730	46.07	64
National Natural Science Foundation of China	195	9508	48.76	40
UK Research and Innovation	109	11831	108.54	35
National Institute of Diabetes and Digestive and Kidney Diseases	92	2770	30.11	21
Medical Research Council	84	10849	129.15	30
National Institutes of Health Research	69	8196	118.78	24
European Union	66	3358	53.61	21
Wellcome Trust	57	7805	136.93	21
National Heart, Lung, and Blood Institute	55	5703	103.69	19

Table 3
The top 10 active institutions.

Rank	Institution	Counts	% Of 6266	Citations	Average Citations	H-index	Centrality
1	Harvard University	213	3.40 %	10388	48.77	48	0.13
2	University of London	182	2.90 %	12618	68.95	42	0.03
3	University of California System	172	2.74 %	5959	34.65	38	0.06
4	Institut National de la Santé et de la Recherche Médicale	138	2.20 %	6126	44.39	33	0.03
5	University of Paris Cite	125	1.99 %	5360	42.88	34	0.03
6	Assistance Publique - Hôpitaux de Pari	122	1.95 %	4513	36.99	33	0.02
7	Egyptian Knowledge Bank	114	1.82 %	1838	16.12	22	0.06
8	Huazhong University of Science and Technology	103	1.64 %	30657	297.64	35	0.03
9	University of Oxford	96	1.53 %	9153	95.34	29	0.11
10	Johns Hopkins University	92	1.46 %	2911	31.64	26	0.06

Table 4
The top 10 authors and Co-Cited authors.

Rank	Author	Country/Region	Counts	Citations	H-index	Co-Cited author	Country/Region	Citations
1	Khunti,K	England	36	2045	17	Zhou F	China	1025
2	Holl,R W.	Germany	17	213	7	Guan W	China	936
3	Cariou,B	France	14	990	10	Huang CL	China	718
4	Rizzo,M	Italy	14	317	10	Wu ZY	China	502
5	Schaan,BD.	Brazil	13	167	4	Wang DW	China	493
6	Wargny, M	France	13	975	10	Richardson S	England	451
7	Telo,GHH	Brazil	12	164	4	Grasselli G	Italy	412
8	Sattar,N	Scotland	12	1176	9	Williamson EJ	England	338
9	Rudramurthy,S.M	India	12	523	8	Yang J	China	337
10	Alessi,J	Brazil	12	164	4	Wu CM	China	330

different disciplines. Fig. 3 shows the distribution of topics on COVID-19 and DM. The bold yellow line indicates that research in Molecular, Biology, Genetics journals is frequently cited in Molecular, Biology, Immunology journals. The bold green line indicates that research in Molecular, Biology, Genetics and Health, Nursing, Medicine journals is predominantly cited in Medicine, Medical, Clinical journals.

3.5. Analysis of cited references

Fig. 4B: The timeline map of co-cited references in COVID-19 and DM. The cluster labels are keywords clustered using the logarithmic likelihood ratio algorithm.Table 6 shows the Top 10 co-cited references; these publications constitute the foundational knowledge base for COVID-19 and DM, playing a crucial role in its development. Zhou F 's article, which reported the clinical course of hospitalized patients who died and the associated risk factors, has the highest number of citations (1007) [79].

Through the visualized co-cited references map, the evolution of a particular research theme can be traced by analyzing key nodes, clusters, and color variations. Cluster analysis of cited references' keywords resulted in 10 distinct clusters, as visualized in Fig. 4A. These cluster labels are generated using the log-likelihood ratio method, and the distinct dominant colors of the clusters and labels reveal their varying periods of flourishing. The significant cluster structure, indicated by an average Q value of 0.5207 ($Q > 0.3$), and the high degree of homogeneity among cluster members, as evidenced by an average S value of 0.8432 ($S > 0.7$), further indicate the reliability of the clustering analysis. In this co-cited reference visualization map, each node represents a cited reference, with node size proportional to its citation count. The color surrounding the node indicates the year of citation, transitioning from deep purple (Q1 2020) to yellow (Q2 2024). Nodes encircled with a purple circle indicate centrality score exceeding 0.1, signifying their significant role

Table 5
The top 20 journals and Co-Cited journals.

Rank	Counts	% Of 6266	Journal	JIF (2023)	JIF quartile (2023)	Co-Cited Journal	Citations	Centrality	JIF (2023)	JIF quartile (2023)
1	252	4.02 %	PLOS ONE	2.9	Q1	Lancet	3197	0.22	98.4	Q1
2	124	1.97 %	Diabetes Research and Clinical Practice	6.1	Q1	New England Journal of Medicine	3004	0.16	96.2	Q1
3	111	1.77 %	Scientific Reports	3.8	Q1	JAMA-Journal of the American Medical Association	2827	0.12	63.1	Q1
4	99	1.57 %	Journal of Clinical Medicine	3.0	Q1	PLOS ONE	1993	0.13	2.9	Q1
5	97	1.54 %	Frontiers in Medicine	3.1	Q1	Diabetes Care	1832	0.06	14.8	Q1
6	94	1.50 %	International Journal of Environmental Research and Public Health	2.2	Q3	BMJ-British Medical Journal	1577	0.04	93.6	Q1
7	87	1.38 %	Frontiers in Public Health	3.0	Q2	Clinical Infectious Disease	1422	0.06	8.2	Q1
8	83	1.32 %	BMJ Open	2.4	Q1	Nature	1356	0.14	50.5	Q1
9	80	1.27 %	Frontiers in Endocrinology	3.9	Q2	Journal of Medical Virology	1189	0.11	6.8	Q1
10	66	1.05 %	Diabetes Care	14.8	Q1	Diabetes Research and Clinical Practice	1165	0.03	6.1	Q1
11	64	1.02 %	BMC Infectious Disease	3.4	Q2	Scientific Reports	1069	0.03	3.8	Q1
12	56	0.89 %	Journal of Medical Virology	6.8	Q1	Lancet Diabetes & Endocrinology	1050	0.03	44.0	Q1
13	56	0.89 %	Vaccines	5.2	Q1	Lancet Respiratory Medicine	1010	0.05	38.7	Q1
14	55	0.87 %	Healthcare	2.4	Q2	International Journal of Infectious Diseases	990	0.04	4.8	Q1
15	45	0.71 %	ACTA Diabetologica	3.1	Q2	The Lancet Infectious Disease	879	0.03	36.4	Q1
16	45	0.71 %	International Journal of Infectious Diseases	4.8	Q1	MMWR-Morbidity and Mortality Weekly Reports	876	0	25.4	Q1
17	44	0.70 %	JAMA Network Open	10.5	Q1	JAMA Internal Medicine	871	0.02	22.5	Q1
18	44	0.70 %	BMC Public Health	3.5	Q1	Nature Medicine	823	0.05	58.7	Q1
19	43	0.68 %	Nutrients	4.8	Q1	Diabetes & Metabolic Syndrome: Clinical Research	814	0.02	4.3	Q1
20	41	0.65 %	Nutrition, Metabolism and Cardiovascular Disease	3.3	Q2	Diabetologia	790	0.01	8.4	Q1

within the co-cited references network. These publications may serve as pivotal intermediaries, bridging different clusters. Fig. 4B illustrates the emergence, flourishing, and decline of research related to different clusters over time. Combining the results of cluster analysis and a timeline map of co-cited references reveals two key observations: (1) Cluster #0 labeled "clinical characteristics" and cluster #1 labeled "diabetes" are the clusters with the largest citation proportions, indicating that articles related to these clusters play a significant role in forming the knowledge base and driving the development of COVID-19 and DM. (2)cluster #5, labeled "long COVID" was the latest to emerge (the mean year = 2021), potentially representing the research frontiers in the field. Table 7 lists the top 10 references with the strongest citations within this cluster.

In cluster #5, labeled "long COVID," the four most cited references with the highest burst strengths are pivotal due to their significant citation impact. The titles of these references are as follows: "Post-acute COVID-19 syndrome," "Long COVID: major findings, mechanisms, and recommendations," "High-dimensional characterization of post-acute sequelae of COVID-19," and "Multiple early factors are anticipated post-acute COVID-19 sequelae." Their burst strengths are 12, 11.46, 5.48, and 4.01, respectively, the respective number of citations are 25, 25, 9, and 7 words. These findings underscore their central role in shaping discussions within the cluster on long COVID.

3.6. Analysis of keywords and co-occurrence clusters

In this study, the network visualization diaplays keywords with a co-occurrence frequency greater than 50. The most frequently used search term in this area was "COVID-19." The top 20 keywords in this field by co-occurrence frequency are listed in Table 8 after

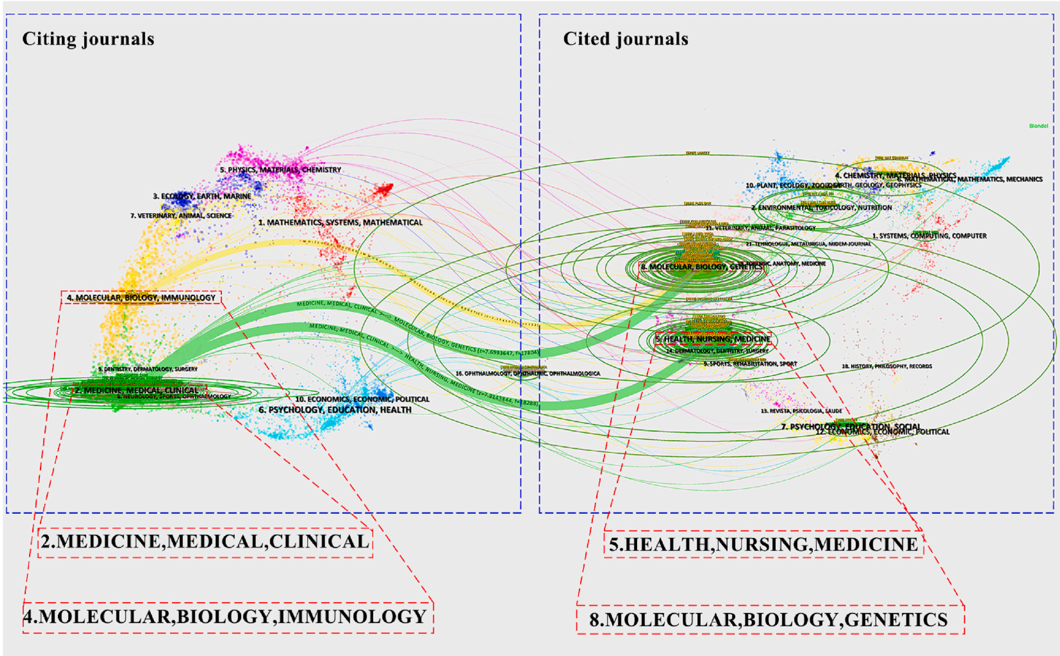

Fig. 3. The dual-map overlay of journals in COVID-19 and DM.

Table 6
The top 10 cited references.

Rank	Reference	Citations	Centrality	Journal	JIF (2023)	First Author	Time
1	Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study	1007	0.12	Lancet	98.4	Zhou F	Quarter 1st,2020
2	Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China	635	0.09	Lancet	98.4	Huang CL	Quarter 1st,2020
3	Clinical characteristics of Coronavirus disease 2019 in China	631	0.08	The New England Journal of Medicine	96.2	Guan W	Quarter 2nd,2020
4	Characteristics of and important lessons from the Coronavirus Disease 2019 (COVID-19) outbreak in China: summary of a report of 72,314 cases from the Chinese Center for Disease Control and Prevention	500	0.03	JAMA-Journal of the American Medical Association	63.1	Wu ZY	Quarter 2nd,2020
5	Clinical characteristics of 138 hospitalized patients with 2019 novel Coronavirus-Infected pneumonia in Wuhan, China	479	0.04	JAMA-Journal of the American Medical Association	63.1	Wang DW	Quarter 1st,2020
6	Presenting characteristics, comorbidities, and outcomes among 5700 patients hospitalized with COVID-19 in the New York City area	380	0.04	JAMA-Journal of the American Medical Association	63.1	Richardson S	Quarter 2nd,2020
7	Risk factors associated with acute respiratory distress syndrome and death in patients with coronavirus disease 2019 pneumonia in Wuhan, China	337	0.04	JAMA Internal Medicine	22.5	Wu CM	Quarter 3rd,2020
8	A novel Coronavirus from patients with pneumonia in China, 2019	327	0.06	The New England Journal of Medicine	96.2	Zhu N	Quarter 1st,2020
9	Factors associated with COVID-19-related death using OpenSAFELY	318	0.03	Nature	50.5	Williamson EJ	Quarter 3rd,2020
10	Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study	293	0.03	Lancet Respiratory Medicine	38.7	Yang XB	Quarter 2nd,2020

excluding broad, search terms, and synonyms were merged.

The three most researched keywords on COVID-19 and DM are "risk factor,"" clinical outcome," and " mortality." The top 75 keywords with strong burst strength on COVID-19 and DM are presented in Fig. 5, with the greatest burst strength keywords being "pneumonia." The burst detection list shows a blue line indicating the timeline and red segments indicate the time period encompassing the start and end years, as well as the duration of the burst [48]. These topics with high burst strength can reflect the research trends

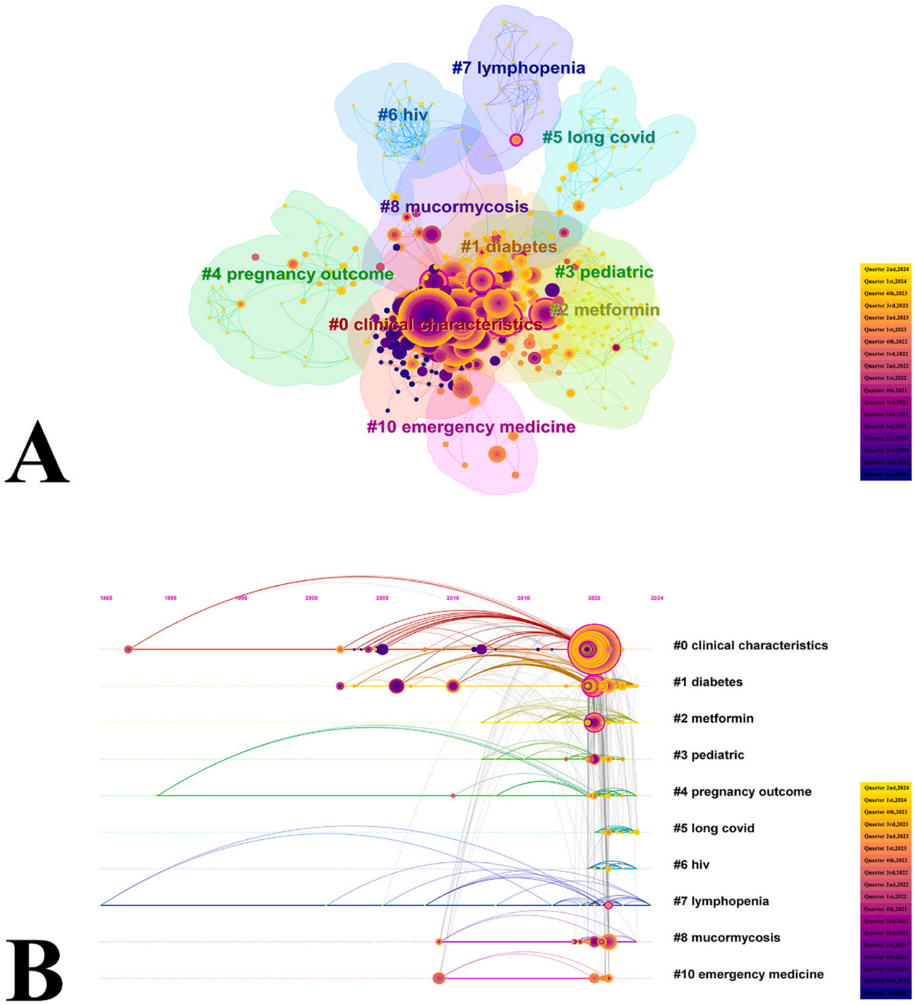

Fig. 4. A: Clusters map of co-cited references in COVID-19 and DM.

and frontiers in the corresponding period. In 2020, the terms "acute respiratory syndrome," "ace2," and "clinical characteristics" demonstrated high burst strengths of 24.58, 24.47, and 22.57, respectively. In 2021, the burst strength of the keywords "guidelines," "mechanisms," and "states" was 6.91, 6.04, and 5.89. In 2022, the terms "COVID-19 vaccine," "primary care" and "depression" showed high burst strengths of 10.89, 8.8, and 6.36 respectively. From 2023 to the present, the keywords with the highest burst strengths are "metabolic syndrome" (6.38), "long COVID" (5.48), and "pregnancy" (5.44). Following keyword analysis, the keywords were further clustered to analyze trends in research. Fig. 6 shows the clusters of research hotspots in this field. The Q value was 0.818 ($Q > 0.3$), and the S value was 0.9446 ($S > 0.7$); thus, the clustering was reliable. In this visualized cluster analysis of keyword co-occurrence, each node represents a keyword, with node size proportional to its frequency. Similarly, distinct colors represent distinct clusters. Based on keyword cluster analysis, cluster #0, labeled "management", and cluster #1, labeled "mortality" are the largest clusters, representing the hottest research topics in COVID-19 and DM. and cluster #11, labeled "long COVID", cluster #9, labeled "gestational diabetes", cluster #8, labeled "mental health" are the most recently emerged clusters, with a mean year of emergence of 2021.

We further analyzed the transfer of research hotspots based on keyword analysis. Initially, during the early stages of the pandemic, research primarily centered on elucidating the impact of diabetes as a comorbidity on COVID-19 pneumonia, encompassing its clinical manifestations, incidence, prognosis, and the intricate interplay of underlying pathophysiological mechanisms. As research progressed, the focus shifted towards investigating the heterogeneity within the diabetic population, exploring the specific responses of different patient types, and acknowledging the unique characteristics and vulnerabilities of each subgroup. Following the advent and widespread application of specific anti-COVID-19 medications and vaccines, the research landscape further evolved, with increased emphasis on the effects of pharmacotherapeutic interventions and vaccinations on glycemic control systems, disease progression, and overall prognosis in diabetic individuals. As the pandemic transitioned towards a less acute phase, research efforts have turned towards investigating the long-term implications of COVID-19 recovery on metabolic function, immune function, cardiovascular function, and other relevant aspects in diabetic patients, including elucidating the mechanisms underlying these persistent effects. Through this

Table 7
The top 10 burst references in cluster #5, labeled "long COVID."

Rank	Reference	Burst	Citations	Journal	JIF (2023)	Author	Time
1	Post-acute COVID-19 syndrome	12	25	Nature Medicine	58.7	Nalbandian A	Quarter 2nd,2021
2	Long COVID: major findings, mechanisms and recommendations	11.46	20	Nature Reviews Microbiology	69.2	Davis HE	Quarter 1st,2023
3	High-dimensional characterization of post-acute sequelae of COVID-19	5.48	9	Nature	50.5	Al-Aly Z	Quarter 2nd,2021
4	Multiple early factors anticipate post-acute COVID-19 sequelae	4.01	7	Cell	45.5	Su YP	Quarter 1st,2022
5	Risk factors associated with post-COVID-19 condition a systematic review and meta-analysis	0	6	Jama Internal Medicine	22.5	Tsampasian V	Quarter 2nd,2023
6	Risk and protectivefactors for COVID-19 morbidity, severity, and mortality.	0	4	Clinical Reviews In Allergy & Immunology	8.4	Zhang JJ	Quarter 1st,2023
7	Long COVID: post-acute sequelae of COVID-19 with a cardiovascular focus	0	3	European Heart Journal	37.6	Raman B	Quarter 1st,2022
8	Short-term and long-term rates of post-acute Sequelae of SARS-CoV-2 infection a systematic review	0	3	JAMA Network Open	10.5	Groff D	Quarter 4th,2021
9	A clinical case definition of post-COVID-19 condition by a Delphi consensus	0	2	The Lancet Infectious Diseases	36.4	Soriano JB	Quarter 2nd,2022
10	Symptoms and risk factors for long COVID in non-hospitalized adults	0	25	Nature Medicine	58.7	Subramanian A	Quarter 3rd,2022

Table 8
The top 20 keywords.

Rank	Keywords	Occurrences	Centrality	Rank	Keywords	Occurrences	Centrality
1	risk factor	833	0.12	11	glucose control	158	0.01
2	clinical outcome	538	0.11	12	obesity	156	0.23
3	mortality	536	0.01	13	ace2	135	0.03
4	clinical characteristics	307	0.05	14	cardiovascular disease	126	0.01
5	infection	305	0.06	15	diagnosis	119	0.02
6	management	239	0.13	16	children	115	0.08
7	association	229	0.19	17	wuhan	114	0.10
8	prevalence	222	0.31	18	receptor	99	0.02
9	severity	187	0.06	19	pandemic	93	0.01
10	pneumonia	172	0.27	20	inflammation	91	0.04

evolving research journey, the central objective has remained steadfastly focused on exploring a broad spectrum of therapeutic interventions, evaluating their efficacy, and ultimately determining their impact on clinical outcomes. Furthermore, "metabolic syndrome," "long COVID," and " pregnancy " are still likely to be the hotspots and frontiers of research in the future.

4. Discussion

Since the emergence of COVID-19 in late 2019, research related to the pandemic has garnered significant attention, resulting in a rapid proliferation of publications accompanied by a surge in citations [78]. Studies have shown that COVID-19-related papers exhibit a significantly higher proportion of highly cited articles than the global average, and this trend is evident across multiple fields, countries, and journal impact factor ranges. This citation advantage poses challenges to bibliometric analysis, primarily manifested in the imbalance of Highly Cited Papers, distorted journal impact factors, and inaccurate research evaluations [57]. To mitigate this negative influence, this study extended the citation time window and segmented it to count citations in different time periods separately, aiming to more accurately reflect the changing trend of a paper's influence. As far as we know, most previous bibliometric publications on COVID-19 and DM have been analyzed based on time slices of one year. Considering the rapid growth of publications in this field, this paper analyzes publications by quarter. Such a fine time scale can more accurately represent the evolution of trends in COVID-19 and DM.

In previously published bibliometric studies on COVID-19, Wen et al. analyzed COVID-19 imaging literature from the first 30 months in the field. They found that research trends include assessment of clinical imaging features, AI-based differential diagnosis, vaccination, and prognosis prediction. Future directions may focus on COVID-19's impact on other organs and disease diagnosis [75]. Vishwanathan's analysis of the top 100 cited articles in this field indicate that the Center for Disease Prevention and Control and the Columbia University Irving Medical Center in the US published the most publications, with four each, and that China had the highest total and average number of citations, despite having the second-highest number of publications [73]. Liu, W. et al. have identified three main research priorities: risk factors & clinical outcomes, ACE2 receptor & cytokine storm, and clinical characteristics &

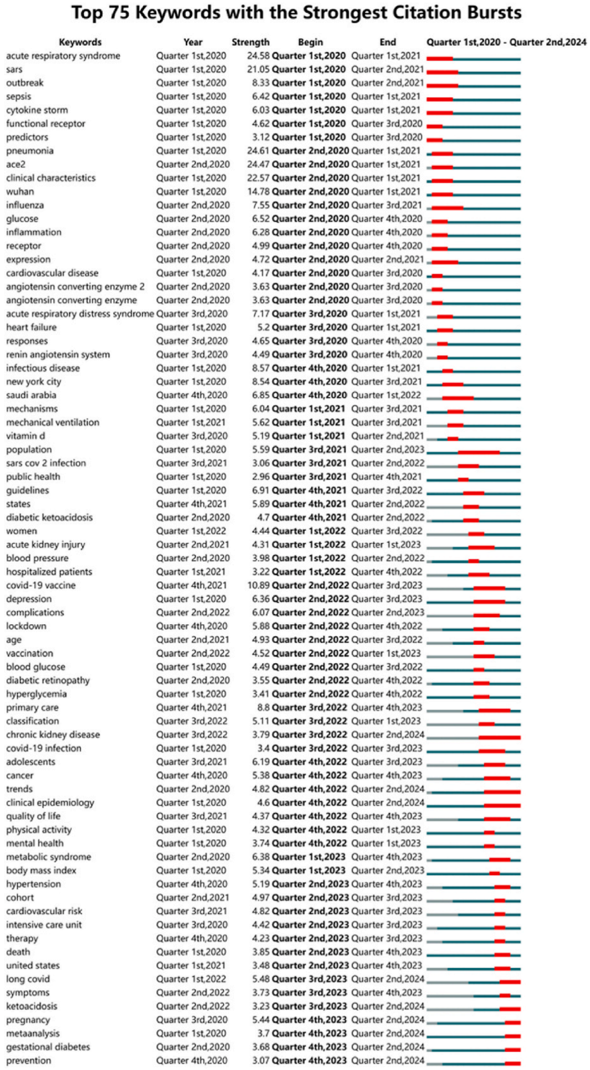

Fig. 5. Top 75 keywords with the strongest citation burst values in COVID-19 and DM research.

epidemiology, with hyperglycaemia, obesity, prognosis, and cytokine storm being the most researched topics [56]. Our study generally aligned with these findings, but we further evaluated the evolving research trends in the field of COVID-19 and DM and further predicted future research frontiers.

The analysis of the number of publications demonstrates the significant influence of articles published in the first quarter of 2020 on the advancement of this field, forming the foundation of knowledge within it. In the national analysis, publications from China and the USA accounted for about 38.41 % of all publications. Furthermore, while not producing the highest number of publications, China boasts the highest average citation count and H-index. This indicates the relative maturity of research in this field and a higher level of recognition for its output. Among the top 10 most productive institutions, only Harvard University and University of Oxford exhibit betweenness centrality exceeding 0.1, signifying their pivotal role in facilitating knowledge sharing and influencing multiple institutions through their extensive collaborations within the field of COVID-19 and DM. Further, Huazhong University of Science and Technology exhibits the highest average citation count and H-index, a potential connection to its location in Wuhan, China, which may be related to the first COVID-19 outbreak there [81]. The result of analysis of institutions highlights the significant contribution of Huazhong University of Science and Technology to this research field, as reflected in its high number of highly cited publications. A summary of research hotspots can be drawn from the top cited papers published by Huazhong University of Science and Technology, primarily centering on the impact of DM as a predictor of prognosis in patients with COVID-19 on their clinical management practices and clinical outcomes [42,79]. Most of the top 10 cited authors was from China and published mainly in the early years of the pandemic. These articles primarily have reported the clinical characteristics, laboratory risk factors, and clinical outcomes of Wuhan epidemic patients [37,42,79]. Based on the above analysis, we conclude that China and the USA are quantitatively and influentially leading the world in this field. In the analysis of journals, the knowledge base of the field of COVID-19 and DM is primarily is

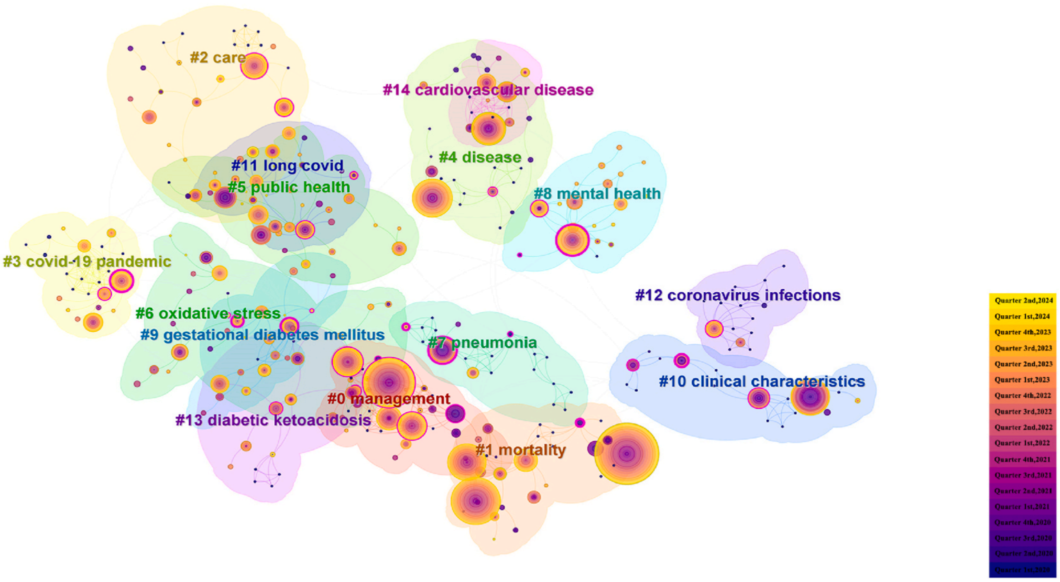

Fig. 6. The knowledge map of keyword clustering.

constituted by journals in the areas of "Molecular, Biology, Genetics" and "Health, Nursing, Medicine." However, current research in this field primarily published in journals in the areas of "Molecular, Biology, Immunology," and "Medicine, Medical, Clinical."

In the analysis of keywords, "risk factors" occurs as the most frequent keyword and has a high centrality of 0.12, identifying a central position for the mapped knowledge domain. There are complex mechanisms between DM and COVID-19. On the one hand, the researchers not only had discovered that diabetics were at higher risk of suffering from fatal or intensive care unit-treated COVID-19 pneumonia and related health complications compared to non-diabetics but also had a higher mortality rate [7,69,80]. This, suggests a direct connection between DM and the severity and prognosis of COVID-19 pneumonia. On the other hand, COVID-19 has been shown to bind to angiotensin-converting enzyme 2 (ACE2) receptors in pancreatic islet cells, damaging them to downregulate surface ACE2 receptors, which in turn led to cytokine inflammation, B-cell apoptosis, and ultimately reduced insulin secretion [6]. Also, infection with COVID-19 results in a vicious cycle of hyperglycaemia and an inflammatory response caused by viral inflammation and an immune response that impairs insulin sensitivity and dysregulates glucose metabolism [46]. Overall, COVID-19 leads to metabolic disturbances and impaired glucose homeostasis, resulting in new-onset DM or exacerbating established metabolic disease, triggering acute hyperglycaemic crises and worsening the prognosis of patients with poorly controlled DM [47,70]. Therefore, DM is one of the most noteworthy risk factors for COVID-19 [49].

The keywords analysis exhibited a distinct trajectory, shifting from the initial emphasis on understanding the impact of diabetes on COVID-19 infection and its associated pathophysiological mechanisms to a focus on analyzing the differential responses of diverse patient populations. Subsequently, research progressed to examine the effects of medications and vaccines, as well as the long-term consequences of COVID-19 in diabetic individuals. Throughout this research endeavor, the exploration of diverse therapeutic interventions, their efficacy, and ultimate outcomes have consistently remained a paramount focus. In the early years of the pandemic, many articles reported the presence of DM as a clinical feature of COVID-19 and observed a significant impact of DM on the prevalence of COVID-19 [54]. As have demonstrated by experts worldwide, individuals with COVID-19 comorbid DM have greater levels of leukocyte count, neutrophil count, high-sensitivity C-reactive protein, and enhanced risk of mortality than those without DM [41,77]. Therefore, DM is considered a risk factor for poor prognosis in COVID-19. Notably, patients with COVID-19 combined with newly diagnosed DM had a higher risk of death when compared to patients with known DM [77]. Furthermore, studies have shown that ACE2 is associated with the development and prognosis of COVID-19 in combination with DM and that inhaled corticosteroids (ICS) are related to reduced ACE2 expression. This finding not only indicated that ICS may reduce the susceptibility to SARS-CoV-2 infection and the incidence of COVID-19, thereby improving their prognosis but further suggests that treatments targeting ACE2 may be an effective therapeutic target [25,64]. During the different phases of the COVID-19 epidemic, different managements were taken to manage patients, with different implications for both patients and physicians. During the pandemic, telemedicine has emerged rapidly. The use of remote continuous blood glucose monitoring for patients with COVID-19 combined with DM in isolation not only allowed for tracking blood glucose trends instantly to prevent dramatic changes in blood glucose but also reduces the times healthcare workers enter the isolation area, reducing the risk of infection for healthcare workers [72].

The combined application of co-cited reference clustering, keyword clustering, and keyword burst detection can be effectively utilized to identify the current state of research, emerging trends, and potential future research frontiers in the field of COVID-19 and DM [21]. Cluster analysis of co-cited references reveals that cluster #5, labeled "long COVID," represents the most recent cluster to emerge. Analysis of keyword bursts showed that the most recent bursts keywords were "metabolic syndrome", "long COVID", and "pregnancy". Moreover, keyword cluster analysis indicates that cluster #11, labeled long covid , cluster #9, labeled gestational diabetes , cluster #8, labeled mental health are the most recent clusters to emerge. Combining the results of co-cited reference clustering, keyword clustering, and keyword burst detection suggests that "metabolic syndrome," "long COVID," and "gestational diabetes" are likely to be current research hotspots and frontiers in the field of COVID-19 and DM.

Metabolic syndrome is a complex metabolic disorder characterized by a cluster of conditions, including obesity, high blood pressure, high blood sugar, and high blood lipids [28]. As researchers across multiple disciplines delve deeper into the epidemiology, pathogenesis, and comorbidities of COVID-19, the association between COVID-19 and metabolic syndrome has garnered increasing attention. Metabolic syndrome components include abnormal glucose metabolism, the most closely linked to COVID-19. Early research focused on diabetes and other components of metabolic syndrome on COVID-19 severity [36]. In 2020, studies suggested a correlation between patients with severe hypertension, chronic kidney disease, obstructive sleep apnea, and abnormal metabolic states (including diabetes and obesity) and an increased risk of COVID-19 mortality [28]. Subsequent research has firmly established metabolic syndrome as a risk factor for COVID-19 severity and a predictor of unfavorable outcomes [11]. Further investigations have revealed a higher incidence of hyperglycemia in COVID-19 patients, even among those without a prior history of diabetes, with the potential for persistent metabolic abnormalities following recovery [63,67]. Moreover, research indicates that COVID-19 infection can act as a trigger for increased incidence and severity of diabetic ketoacidosis in children with DM, potentially due to increased damage to pancreatic β-cells and the need for higher insulin doses [67]. Recent studies have uncovered that COVID-19 invasion can impact lipid metabolic pathways and related genes, presenting a potential target for future novel therapeutic strategies. These discoveries are crucial for understanding the complex relationship between COVID-19 and metabolic syndrome, paves the way for more effective prevention and treatment.

Long COVID, also known as Post-Acute Sequelae of COVID-19(PASC), refers to the persistence of symptoms affecting multiple organ systems in individuals following an acute COVID-19 infection. These symptoms can last for months or even longer, significantly impacting quality of life [35]. The mechanisms underlying long COVID are complex, and current understanding often focuses on explaining specific symptoms. A 2021 study identified persistent endothelial dysfunction, female sex, and severe clinical presentation requiring oxygen supplementation during acute COVID-19 infection as independent risk factors for long COVID syndrome. Furthermore, the study suggested that some long COVID symptoms, particularly non-respiratory symptoms, are primarily driven by persistent endothelial dysfunction [61]. Further research has revealed a significant burden of insoluble fibrin amyloid microclots in the circulation of long COVID patients. These microclots trap inflammatory molecules, leading to a persistent inflammatory response [66]. It is notable that, some inflammatory factors inhibit clot breakdown, resulting in fibrinolysis failure, even in the absence of abnormalities on conventional pathological tests. This phenomenon could explain the chronic fatigue, dyspnea, or cognitive impairment observed in long COVID patients [51]. Additionally, these microclots may not only impair pancreatic function, leading to insufficient insulin secretion, but also exacerbate insulin resistance and contribute to T2DM due to the associated inflammatory response [3,65]. Therefore, post-acute COVID-19 care should encompass the identification and management of DM.

Gestational diabetes mellitus (GDM) is an abnormal glucose tolerance condition that arises during pregnancy, characterized by normal pre-pregnancy glucose levels but the development of hyperglycemia during gestation. GDM is typically diagnosed between 24 and 28 weeks of gestation using an oral glucose tolerance test [68]. COVID-19 impacts gestational diabetes bidirectionally [74]. On the one hand, the COVID-19 pandemic has led to an increase in GDM incidence due to factors such as lifestyle changes and increased psychological stress [76]. Additionally, risk factors for GDM, such as BMI and obesity rates, have also risen among pregnant women [34]. On the other hand, pregnant women with GDM who contract COVID-19 may experience more severe illness and have a higher likelihood of intensive care [30]. Due to these factors, researchers have advocated for enhanced prenatal management, providing telemedicine services, and promoting vaccination to safeguard the health of both the mother and the fetus [5,9,43].

5. Limitations

There were some limitations to this study. First, Citespace only analyzes titles, abstracts, keywords, topics, etc., and not the complete text, which may lead to missing information. Secondly, this software cannot distinguish between the first and corresponding authors. Countries and institutions are analyzed based on all co-authors, not the first or corresponding authors. Third, the quality of individual studies cannot be evaluated bibliometrically due to variations in citation metrics over time, which suggests that relatively recent publications may be cited less than earlier ones, mainly owing to the publication date. Additionally, there are some drawbacks to the Web of Science(WoS) data. Firstly, access to WoS data requires a subscription and is not publicly available. Secondly, WoS may have incomplete coverage of non-English literature, and since this study is currently limited to English-language publications, this may affect the global representativeness of the research findings, especially concerning a global issue like COVID-19 [4]. Furthermore, some funding information in WoSCC database faces several limitations: discrepancies in the time coverage of funding information across different journal indexes; insufficient coverage of funding information for non-English publications; uneven recording of funding information across different document types; and potential omissions or inaccuracies due to variability in search strategies and data quality [50,58]. To enhance the comprehensiveness and international perspective of future research, consideration will be given to incorporating a broader range of database resources. Such limitations marginally affect the general results but are unlikely to alter the critical trends suggested in this article. Therefore, this study will help relevant researchers understand the hot spots, trends, and research frontiers on COVID-19 and DM.

6. Conclusion

As the COVID-19 epidemic spreads worldwide, we have analyzed the current publications in the field quarterly. The results will help clinicians to understand the current state of research and the latest trends on COVID-19 and DM. We have identified three main directions for future research in this area.

1 Exploring the complex relationship between metabolic syndrome and COVID-19, revealing the impact of COVID-19 infection on metabolic pathways, and identifying potential targets for future therapeutic strategies
2 Investigating the pathophysiological mechanisms underlying Long COVID and identifying associated diseases, and further identifying management strategies for relevant populations.
3 Researching the bidirectional impact of COVID-19 on GDM and its associated factors, and further investigating management strategies that can mitigate this impact during the COVID-19 pandemic.

This study will contribute to understanding its clinical features, prognosis, prevention, and treatment and provide additional attention and support to such patients.

Data availability statement

All data used in this study were sourced from the WoSCC, which requires a subscription for access. The data are not deposited in a publicly available repository but are fully presented in this manuscript to support the conclusions and reproducibility of the research.

CRediT authorship contribution statement

Xunlan Zhang: Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Ru Wen:** Writing – review & editing. **Hengzhi Chen:** Software. **Jian Liu:** Writing – review & editing. **Yu Wu:** Formal analysis, Data curation. **Min Xu:** Project administration. **Rongpin Wang:** Visualization, Validation, Supervision. **Xianchun Zeng:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Xianchun Zeng reports financial support was provided by National Natural Science Foundation of China and Guiyang Municipal Science and Technology Bureau. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] M. Apicella, et al., COVID-19 in people with diabetes: understanding the reasons for worse outcomes, Lancet Diabetes Endocrinol. 8 (9) (2020) 782–792, https://doi.org/10.1016/S2213-8587(20)30238-2. Sep. 2020.
[2] Y. Assenov, et al., Computing topological parameters of biological networks, Bioinformatics 24 (2) (2008) 282–284, https://doi.org/10.1093/bioinformatics/btm554 (Jan. 2008).
[3] R. Astin, et al., Long COVID: mechanisms, risk factors and recovery, Exp. Physiol. 108 (1) (2023) 12–27, https://doi.org/10.1113/EP090802. Jan. 2023.
[4] T. Asubiaro, et al., Regional disparities in Web of science and Scopus journal coverage, Scientometrics 129 (3) (2024) 1469–1491, https://doi.org/10.1007/s11192-024-04948-x. Mar. 2024.
[5] A. Aziz, et al., Telehealth for high-risk pregnancies in the setting of the COVID-19 pandemic, Am. J. Perinatol. 37 (8) (2020) 800–808, https://doi.org/10.1055/s-0040-1712121 (Jun. 2020.
[6] L. Bao, et al., The pathogenicity of SARS-CoV-2 in hACE2 transgenic mice, Nature 583 (7818) (2020) 830–833, https://doi.org/10.1038/s41586-020-2312-y. Jul. 2020.
[7] E. Barron, et al., Associations of type 1 and type 2 diabetes with COVID-19-related mortality in England: a whole-population study, Lancet Diabetes Endocrinol. 8 (10) (2020) 813–822, https://doi.org/10.1016/S2213-8587(20)30272-2. Oct. 2020.
[8] C. Birkle, et al., Web of Science as a data source for research on scientific and scholarly activity, Quantitative Science Studies 1 (1) (2020) 363–376, https://doi.org/10.1162/qss_a_00018. Feb. 2020.
[9] H. Blakeway, et al., COVID-19 vaccination during pregnancy: coverage and safety, Am. J. Obstet. Gynecol. 226 (2) (2022) 236.e1–236.e14, https://doi.org/10.1016/j.ajog.2021.08.007. Feb. 2022.
[10] S.P. Borgatti, et al., Network analysis in the social sciences, Science 323 (5916) (2009) 892–895, https://doi.org/10.1126/science.1165821. Feb. 2009.
[11] B.T. Bradley, et al., Histopathology and ultrastructural findings of fatal COVID-19 infections in Washington State: a case series, Lancet (London, England) 396 (2020) 320–332, https://doi.org/10.1016/S0140-6736(20)31305-2, 10247 (Aug. 2020).
[12] H. Cao, et al., Bidirectional causal associations between type 2 diabetes and COVID-19, J. Med. Virol. (2022), https://doi.org/10.1002/jmv.28100 (Aug. 2022).
[13] CDC COVID-19 Response Team, Preliminary estimates of the prevalence of selected underlying health conditions among patients with coronavirus disease 2019 - United States, february 12-march 28, 2020, MMWR. Morbidity and mortality weekly report 69 (13) (2020) 382–386, https://doi.org/10.15585/mmwr.mm6913e2. Apr. 2020.
[14] A. Ceriello, et al., Why is hyperglycaemia worsening COVID-19 and its prognosis? Diabetes Obes. Metabol. 22 (10) (2020) 1951–1952, https://doi.org/10.1111/dom.14098. Oct. 2020.
[15] C. Chen, A glimpse of the first eight months of the COVID-19 literature on microsoft academic graph: themes, citation contexts, and uncertainties, Frontiers in Research Metrics and Analytics 5 (Dec. 2020) (2020) 607286, https://doi.org/10.3389/frma.2020.607286.
[16] C. Chen, CiteSpace II: detecting and visualizing emerging trends and transient patterns in scientific literature, J. Am. Soc. Inf. Sci. Technol. 57 (2006) (2006) 359–377.
[17] C. Chen, CiteSpace II: detecting and visualizing emerging trends and transient patterns in scientific literature, J. Am. Soc. Inf. Sci. Technol. 57 (Feb. 2006) (2006) 359–377, https://doi.org/10.1002/asi.20317.
[18] C. Chen, et al., Emerging trends and new developments in regenerative medicine: a scientometric update (2000 - 2014), Expet Opin. Biol. Ther. 14 (9) (2014) 1295–1317, https://doi.org/10.1517/14712598.2014.920813. Sep. 2014).

[19] C. Chen, et al., Emerging trends in regenerative medicine: a scientometric analysis in CiteSpace, Expet Opin. Biol. Ther. 12 (5) (2012) 593–608, https://doi.org/10.1517/14712598.2012.674507 (May 2012),.
[20] C. Chen, Mapping Scientific Frontiers: the Quest for Knowledge Visualization, Springer, 2013.
[21] C. Chen, Predictive effects of structural variation on citation counts, J. Am. Soc. Inf. Sci. Technol. 63 (Mar. 2012) (2012) 431–449, https://doi.org/10.1002/asi.21694.
[22] C. Chen, Searching for intellectual turning points: progressive knowledge domain visualization, Proc. Natl. Acad. Sci. U.S.A. 101 (Suppl 1, Suppl 1) (2004) 5303–5310, https://doi.org/10.1073/pnas.0307513100. Apr. 2004).
[23] C. Chen, et al., The structure and dynamics of cocitation clusters: a multiple-perspective cocitation analysis, J. Am. Soc. Inf. Sci. Technol. 61 (7) (2010) 1386–1409, https://doi.org/10.1002/asi.21309. Jul. 2010.
[24] C. Chen, M. Song, Visualizing a field of research: a methodology of systematic scientometric reviews, PLoS One 14 (10) (2019) e0223994, https://doi.org/10.1371/journal.pone.0223994. Oct. 2019.
[25] J. Chen, et al., Individual variation of the SARS-CoV-2 receptor ACE2 gene expression and regulation, Aging Cell 19 (7) (2020) e13168, https://doi.org/10.1111/acel.13168. Jul. 2020.
[26] Y. Chen, et al., Principles and Applications of Analyzing a Citation Space, Publisher: Science Press, 2014.
[27] K. Cheng, et al., Mapping knowledge landscapes and emerging trends of the links between bone metabolism and diabetes mellitus: a bibliometric analysis from 2000 to 2021, Front. Public Health 10 (2022) (2022) 918483, https://doi.org/10.3389/fpubh.2022.918483.
[28] S. Chiappetta, et al., COVID-19 and the role of chronic inflammation in patients with obesity, Int. J. Obes. 44 (8) (2020) 1790–1792, https://doi.org/10.1038/s41366-020-0597-4. Aug. 2020.
[29] I.E. Corrales-Reyes, et al., COVID-19 and diabetes: analysis of the scientific production indexed in Scopus, Diabetes Metabol. Syndr. 15 (3) (2021) 765–770, https://doi.org/10.1016/j.dsx.2021.03.002, 2021.
[30] C.A. DeBolt, et al., Pregnant women with severe or critical coronavirus disease 2019 have increased composite morbidity compared with nonpregnant matched controls, Am. J. Obstet. Gynecol. 224 (5) (2021) 510.e1–510.e12, https://doi.org/10.1016/j.ajog.2020.11.022. May 2021.
[31] X. Ding, Z. Yang, Knowledge mapping of platform research: a visual analysis using VOSviewer and CiteSpace, Electron. Commer. Res. 22 (3) (2022) 787–809, https://doi.org/10.1007/s10660-020-09410-7. Sep. 2022).
[32] Q. Dong, et al., Bibliometric and visual analysis of vascular calcification research, Front. Pharmacol. 12 (2021) (2021) 690392, https://doi.org/10.3389/fphar.2021.690392.
[33] Z. Fang, et al., An extensive analysis of the presence of altmetric data for Web of Science publications across subject fields and research topics, Scientometrics 124 (3) (2020) 2519–2549, https://doi.org/10.1007/s11192-020-03564-9, 2020).
[34] L. Ghesquière, et al., Effects of COVID-19 pandemic lockdown on gestational diabetes mellitus: a retrospective study, Diabetes & Metabolism 47 (2) (2021) 101201, https://doi.org/10.1016/j.diabet.2020.09.008 (Mar. 2021.
[35] Global Burden of Disease Long COVID Collaborators, Estimated global proportions of individuals with persistent fatigue, cognitive, and respiratory symptom clusters following symptomatic COVID-19 in 2020 and 2021, JAMA 328 (16) (2022) 1604–1615, https://doi.org/10.1001/jama.2022.18931. Oct. 2022).
[36] J.M. Gregory, et al., COVID-19 severity is tripled in the diabetes community: a prospective analysis of the pandemic's impact in type 1 and type 2 diabetes, Diabetes Care 44 (2) (2021) 526–532, https://doi.org/10.2337/dc20-2260. Feb. 2021.
[37] W.-J. Guan, et al., Comorbidity and its impact on 1590 patients with COVID-19 in China: a nationwide analysis, Eur. Respir. J. 55 (5) (2020) 2000547, https://doi.org/10.1183/13993003.00547-2020 (May 2020.
[38] Y. Han, et al., Working the literature harder: what can text mining and bibliometric analysis reveal? Expet Rev. Proteonomics 16 (2019) 871–873, https://doi.org/10.1080/14789450.2019.1703678, 11–12 (2019),.
[39] He, Z. et al. Hotspots and frontiers in pulmonary arterial hypertension research: a bibliometric and visualization analysis from 2011 to 2020. Bioengineered. 13, 6, 14667–14680. DOI:https://doi.org/10.1080/21655979.2022.2100064.
[40] J.E. Hirsch, An index to quantify an individual's scientific research output, Proc. Natl. Acad. Sci. U.S.A. 102 (46) (2005) 16569–16572, https://doi.org/10.1073/pnas.0507655102. Nov. 2005.
[41] L. Hu, et al., Risk factors associated with clinical outcomes in 323 coronavirus disease 2019 (COVID-19) hospitalized patients in wuhan, nov. 2020),China, Clin. Infect. Dis.: An Official Publication of the Infectious Diseases Society of America 71 (16) (2020) 2089–2098, https://doi.org/10.1093/cid/ciaa539.
[42] C. Huang, et al., Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China, Lancet (London, England) 395 (2020) 10223, https://doi.org/10.1016/S0140-6736(20)30183-5. Feb. 2020), 497–506.
[43] J. Jardine, et al., Maternity services in the UK during the coronavirus disease 2019 pandemic: a national survey of modifications to standard care, BJOG An Int. J. Obstet. Gynaecol. 128 (5) (2021) 880–889, https://doi.org/10.1111/1471-0528.16547. Apr. 2021).
[44] S. Jiang, et al., Evolutionary patterns and research frontiers in neoadjuvant immunotherapy: a bibliometric analysis, Int. J. Surg. 109 (9) (2023) 2774–2783, https://doi.org/10.1097/JS9.0000000000000492 (Sep. 2023),.
[45] Y.L. Katchanov, et al., Comparing the topological rank of journals in Web of science and mendeley, Heliyon 5 (7) (2019) e02089, https://doi.org/10.1016/j.heliyon.2019.e02089 (Jul. 2019).
[46] P. Kazakou, et al., Diabetes and COVID-19; A bidirectional interplay, Front. Endocrinol. 13 (2022) (2022) 780663, https://doi.org/10.3389/fendo.2022.780663.
[47] N.Y. Kim, et al., Acute hyperglycemic crises with coronavirus disease-19: case reports, Diabetes & Metabolism Journal 44 (2) (2020) 349–353, https://doi.org/10.4093/dmj.2020.0091 (Apr. 2020).
[48] J. Kleinberg, Bursty and hierarchical structure in streams, Data Min. Knowl. Discov. 7 (4) (2003) 373–397, https://doi.org/10.1023/A:1024940629314. Oct. 2003),.
[49] H. Koh, et al., Diabetes predicts severity of COVID-19 infection in a retrospective cohort: a mediatory role of the inflammatory biomarker C-reactive protein, J. Med. Virol. 93 (5) (2021) 3023–3032, https://doi.org/10.1002/jmv.26837. May 2021).
[50] Kokol, P. Discrepancies among Scopus and Web of Science, coverage of funding information in medical journal articles: a follow-up study. J. Med. Libr. Assoc. : JMLA. 111,3, 703–708. DOI:https://doi.org/10.5195/jmla.2023.1513.
[51] A. Kruger, et al., Proteomics of fibrin amyloid microclots in long COVID/post-acute sequelae of COVID-19 (PASC) shows many entrapped pro-inflammatory molecules that may also contribute to a failed fibrinolytic system, Cardiovasc. Diabetol. 21 (1) (2022) 190, https://doi.org/10.1186/s12933-022-01623-4. Sep. 2022.
[52] J. Li, C. Chen, CiteSpace: Text Mining and Visualization in Scientific Literature[M], Capital University of Economics and Business Press, Beijing, 2022.
[53] K. Li, et al., Web of Science use in published research and review papers 1997–2017: a selective, dynamic, cross-domain, content-based analysis, Scientometrics 115 (1) (2018) 1–20, https://doi.org/10.1007/s11192-017-2622-5 (2018.
[54] T. Li, et al., Prevalence of malnutrition and analysis of related factors in elderly patients with COVID-19 in Wuhan, China, Eur. J. Clin. Nutr. 74 (6) (2020) 871–875, https://doi.org/10.1038/s41430-020-0642-3 (Jun. 2020.
[55] Y. Li, et al., The published trend of studies on COVID-19 and diabetes: bibliometric analysis, Front. Endocrinol. 14 (Oct. 2023) (2023) 1248676, https://doi.org/10.3389/fendo.2023.1248676.
[56] X. Lin, et al., Mapping global research trends in diabetes and COVID-19 outbreak in the past year: a bibliometric analysis, Ann. Palliat. Med. 11 (4) (2022) 1241–1252, https://doi.org/10.21037/apm-21-2636 (Apr. 2022.
[57] W. Liu, et al., Citation advantage of COVID-19-related publications, J. Inf. Sci. (2023) 01655515231174385, https://doi.org/10.1177/01655515231174385. May 2023.
[58] W. Liu, et al., Funding information in Web of Science: an updated overview, Scientometrics 122 (3) (2020) 1509–1524, https://doi.org/10.1007/s11192-020-03362-3. Mar. 2020),.

[59] W. Liu, The data source of this study is Web of Science Core Collection? Not enough, Scientometrics 121 (3) (2019) 1815–1824, https://doi.org/10.1007/s11192-019-03238-1. Dec. 2019.
[60] X. Liu, et al., Frontier and hot topics in electrochemiluminescence sensing technology based on CiteSpace bibliometric analysis, Biosens. Bioelectron. 201 (Apr. 2022) (2022) 113932, https://doi.org/10.1016/j.bios.2021.113932.
[61] M.M. Maestre-Muñiz, et al., Long-term outcomes of patients with coronavirus disease 2019 at one year after hospital discharge, J. Clin. Med. 10 (13) (2021) 2945, https://doi.org/10.3390/jcm10132945. Jun. 2021).
[62] A. Martín-Martín, et al., Google scholar, microsoft academic, Scopus, dimensions, Web of science, and OpenCitations' COCI: a multidisciplinary comparison of coverage via citations, Scientometrics 126 (1) (2021) 871–906, https://doi.org/10.1007/s11192-020-03690-4 (2021.
[63] J.A. Müller, et al., SARS-CoV-2 infects and replicates in cells of the human endocrine and exocrine pancreas, Nat. Metab. 3 (2) (2021) 149–165, https://doi.org/10.1038/s42255-021-00347-1 (Feb. 2021),.
[64] M.C. Peters, et al., COVID-19-related genes in sputum cells in asthma. Relationship to demographic features and corticosteroids, Am. J. Respir. Crit. Care Med. 202 (1) (2020) 83–90, https://doi.org/10.1164/rccm.202003-0821OC (Jul. 2020.
[65] E. Pretorius, et al., Persistent clotting protein pathology in Long COVID/Post-Acute Sequelae of COVID-19 (PASC) is accompanied by increased levels of antiplasmin, Cardiovasc. Diabetol. 20 (1) (2021) 172, https://doi.org/10.1186/s12933-021-01359-7 (Aug. 2021).
[66] E. Pretorius, et al., Prevalence of symptoms, comorbidities, fibrin amyloid microclots and platelet pathology in individuals with Long COVID/Post-Acute Sequelae of COVID-19 (PASC), Cardiovasc. Diabetol. 21 (Aug. 2022) (2022) 148, https://doi.org/10.1186/s12933-022-01579-5.
[67] I. Rabbone, et al., Has COVID-19 delayed the diagnosis and worsened the presentation of type 1 diabetes in children? Diabetes Care 43 (Aug. 2020) (2020) dc201321, https://doi.org/10.2337/dc20-1321.
[68] D.C. Serlin, R.W. Lash, Diagnosis and Management of Gestational Diabetes Mellitus, vol. 80, American Family Physician, 2009, pp. 57–62, 1 (Jul. 2009).
[69] A.K. Singh, K. Khunti, COVID-19 and diabetes, Annu. Rev. Med. 73 (Jan. 2022) (2022) 129–147, https://doi.org/10.1146/annurev-med-042220-011857.
[70] C. Steenblock, et al., COVID-19 and metabolic disease: mechanisms and clinical management, Lancet Diabetes Endocrinol. 9 (11) (2021) 786–798, https://doi.org/10.1016/S2213-8587(21)00244-8. Nov. 2021.
[71] M.B. Synnestvedt, et al., CiteSpace II: visualization and knowledge discovery in bibliographic databases, AMIA Annual Symposium Proceedings. 2005 (2005) 724–728 (2005.
[72] E. Ushigome, et al., Usefulness and safety of remote continuous glucose monitoring for a severe COVID-19 patient with diabetes, Diabetes Technol. Therapeut. 23 (1) (2021) 78–80, https://doi.org/10.1089/dia.2020.0237 (Jan. 2021).
[73] K. Vishwanathan, et al., Top 100 cited articles on diabetes mellitus and Covid-19: a bibliometric analysis, Diabetes Metabol. Syndr. 15 (4) (2021) 102160, https://doi.org/10.1016/j.dsx.2021.05.033 (2021).
[74] S.Q. Wei, et al., The impact of COVID-19 on pregnancy outcomes: a systematic review and meta-analysis, CMAJ (Can. Med. Assoc. J.): Canadian Medical Association journal = journal de l'Association medicale canadienne 193 (16) (2021) E540–E548, https://doi.org/10.1503/cmaj.202604 (Apr. 2021.
[75] R. Wen, et al., COVID-19 imaging, where do we go from here? Bibliometric analysis of medical imaging in COVID-19, Eur. Radiol. (2023) 1–11, https://doi.org/10.1007/s00330-023-09498-z (Mar. 2023.
[76] C.A. Wilson, et al., The mental health of women with gestational diabetes during the COVID-19 pandemic: an international cross-sectional survey, J. Wom. Health 31 (9) (2022) 1232–1240, https://doi.org/10.1089/jwh.2021.0584, 2022.
[77] Y. Yan, et al., Clinical characteristics and outcomes of patients with severe covid-19 with diabetes, BMJ open diabetes research & care 8 (1) (2020) e001343, https://doi.org/10.1136/bmjdrc-2020-001343. Apr. 2020).
[78] W. Zhao, et al., How has academia responded to the urgent needs created by COVID-19? – a multi-level global, regional and national analysis, Journal of Information Science 50 (1) (2022), https://doi.org/10.1177/01655515221084646.
[79] F. Zhou, et al., Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study, Lancet (London, England) 395 (2020) 1054–1062, https://doi.org/10.1016/S0140-6736(20)30566-3, 10229 (Mar. 2020.
[80] L. Zhu, et al., Association of blood glucose control and outcomes in patients with COVID-19 and pre-existing type 2 diabetes, Cell Metabol. 31 (6) (2020) 1068–1077, https://doi.org/10.1016/j.cmet.2020.04.021, e3.
[81] W.H. Organization, WHO Director-General's opening remarks at the media briefing on COVID-19, Available via, https://www.who.int, 2020.