Postprint: Visual Analysis of Artificial Intelligence for Diabetic Retinopathy

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Abstract

Background In recent years, artificial intelligence (AI) has developed rapidly in the medical field, and its application in diabetic retinopathy (DR) continues to expand. Objective To summarize the application of AI in DR through bibliometric analysis, elucidate the current status, hotspots, and emerging trends of AI-related research in the DR field, and provide ideas for future research. Methods Using the Web of Science database as the source, relevant literature on AI applied to DR from inception to 2022-11-04 was retrieved, and CiteSpace software was used to conduct visual analysis of publication volume, countries, institutions, authors, co-citations, and keywords. Results A total of 1,770 articles were obtained, with the overall publication volume showing an upward trend, peaking at 402 articles in 2021. China ranked first in publication volume (440 articles), and the United Kingdom had the highest betweenness centrality (0.26). The institutional collaboration network map included 436 institutions, represented by Sun Yat-sen University and Capital Medical University. The author collaboration network map included 601 authors, represented by JIA Y and THOMAS H. Three highly cited authors, GULSHAN V, ABRAMOFF M, and TING D, have made important contributions to this field. OPHTHALMOLOGY, INVESTIGATIVE OPHTHALMOLOGY & VISUAL SCIENCE, and IEEE TRANSACTIONS ON MEDICAL IMAGING are the three most influential journals in the field of AI in DR. Hotspots in AI applied to DR research mainly focus on lesion segmentation and DR diagnosis. Prediction of therapeutic efficacy for diabetic macular edema (a complication of DR), DR disease course management, and improving AI algorithm performance may be future research trends. Conclusion Researchers can refer to the research hotspots and trends shown by the visual analysis, focusing on issues related to AI in DR diagnosis, disease course management, and improving AI algorithm performance.

Full Text

Preamble

Visualization Analysis of Artificial Intelligence in Diabetic Retinopathy

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Abstract

Background: In recent years, artificial intelligence (AI) has demonstrated rapid development in the medical field, with its application in diabetic retinopathy (DR) continually expanding.

Objective: To summarize the application of AI in DR through bibliometric analysis and elucidate the current status, hotspots, and emerging trends in AI-related DR research, thereby providing direction for future studies.

Methods: Using the Web of Science database as the source, we searched for literature on AI applications in DR from database inception to November 4, 2022. CiteSpace software was employed to visualize and analyze publication volume, countries, institutions, authors, co-citations, and keywords.

Results: A total of 1,770 papers were obtained, showing an overall increasing trend in publications, with a peak of 402 papers in 2021. China ranked first in publication volume (440 papers), while the United Kingdom exhibited the highest betweenness centrality (0.26). The institutional collaboration network included 436 institutions, represented by Sun Yat-sen University and Capital Medical University. The author collaboration network comprised 601 authors, represented by JIA Y and THOMAS H. Three highly cited authors–GULSHAN

V, ABRAMOFF M, and TING D—have made significant contributions to the field. *Ophthalmology*, *Investigative Ophthalmology & Visual Science*, and *IEEE Transactions on Medical Imaging* are the three most influential journals in AI applications for DR. Research hotspots primarily focus on lesion segmentation and DR diagnosis. Future trends may include efficacy prediction for diabetic macular edema (a DR complication), DR disease management, and improvement of AI algorithm performance.

Conclusion: Researchers can refer to the hotspots and trends identified through this visual analysis, focusing on AI in DR diagnosis, disease management, and algorithm performance improvement.

Keywords: Diabetic retinopathy; Artificial intelligence; CiteSpace; Bibliometrics; Visualization

Introduction

Diabetic retinopathy (DR) is the most common microvascular complication of diabetes and a leading cause of vision impairment and blindness among individuals over 40 years old [?]. The global diabetic population is projected to reach 643 million by 2045 [?], with DR incidence increasing accordingly. Research indicates that 98% of DR-related blindness can be prevented through early screening, diagnosis, and timely treatment [?]. However, this goal remains difficult to achieve due to uneven distribution of medical resources and a limited number of ophthalmologists [?]. In recent years, with advances in computer science, artificial intelligence (AI) has shown rapid development in medicine, with expanding applications in ophthalmology [?, ?]. Given DR’ s high prevalence, severe consequences, and the fact that it can be diagnosed through color fundus photography, DR has become the earliest and most extensively studied ophthalmic disease in AI research [?], though unified understanding and research standards are still lacking.

CiteSpace is an information visualization software developed by Professor Chen Chaomei and his team based on Java [?]. By conducting bibliometric analysis and mapping knowledge domains for literature in specific fields, it enables understanding of disciplinary development processes, current research status, and prediction of future hotspots and trends [?]. This study employs CiteSpace 6.1.R2 to conduct visual analysis of research literature on AI applications in DR, aiming to provide scholars with clearer research direction references and insights for future in-depth studies.

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Methods

1.1 Data Sources and Search Strategy

We searched the Web of Science (WOS) Core Collection database from inception to November 4, 2022. The search strategy was: (TS=("diabetic retinopathy")) AND (TS=("artificial intelligen" *OR " machine intelligen*" OR "machine learn" *OR " deep learn*" OR "transfer learn" *OR " neural learn*" OR "supervised learn" *OR " neural network*" OR "deep network" *OR " neural nets model*" *OR " convolution*" *OR " automat*" OR "unsupervised clustering" OR "big data" OR "natural language process" *OR " robot*" OR "thinking computer system" OR "expert * system" *OR " evolutionary computation*" *OR " hybrid intelligent system*" OR "machine vision" OR "fuzzy logic" OR "random forest" OR "support vector machine" OR "decision-making tree" OR "bayes * network" OR "blockchain" OR "genetic algorithm" OR "K-nearest neighbors")). The search date was November 4, 2022. Document type was filtered as "Article," followed by manual screening to remove reviews, invited papers, duplicates, and articles without authors. A total of 1,770 valid articles were obtained for this study.

1.2.1 Visualization Analysis Method

Using CiteSpace 6.1.R2 software, we analyzed the retrieved English literature on AI applications in DR to examine publication volume, countries, institutions, authors, co-citations, and keywords. We generated quantitative analyses and knowledge maps to reveal the research framework and developmental trajectory, explore current research status, identify hotspots and frontiers, and analyze future directions.

1.2.2 Parameter Settings

Data were imported with a time span from January 2011 to November 2022. Time slice was set to 1 year, "Top N" to 50, and pruning methods included Pathfinder, pruning sliced networks, and pruning the merged network. Node types were sequentially selected as Country, Institution, Author, Cited Author, Cited Journal, Reference, and Keyword, with "Go" clicked to generate visualization maps.

1.2.3 Data Analysis and Judgment Criteria

In knowledge maps, node size represents frequency of occurrence, and line thickness indicates collaboration relationships and strength [?]. Betweenness centrality evaluates node importance; nodes with centrality $ $0.1 are marked purple, indicating popular and important research in the field [?]. Co-citation theory, proposed by Small and Marshakora in 1973 [?], identifies research hotspots, frontiers, and future trends, representing a mainstream paradigm in visual analysis. In clustering maps, Q>0.3 indicates significant clustering structure, S>0.5 suggests reasonable clustering, and S>0.7 implies convincing clustering effects [?].

Burstness detection identifies emergent keywords; red segments in burst maps represent years of keyword emergence.

Results

2.1 Publication Volume Analysis

Changes in publication volume partially reflect field attention, dynamic trends, and future development, indicating research level and maturity [?]. Analysis of English literature on AI in DR revealed an upward trend. 2011–2017 represented the initial stage with small increases, all below 100 papers. In 2018, publications first exceeded 100 (147 papers), subsequently increasing continuously to a peak of 402 papers in 2021. As of November 4, 2022, 312 papers were published (Figure 1 [Figure 1: see original paper]).

2.2 Country Analysis

CiteSpace analysis generated a country collaboration network map for AI in DR research (Figure 2 [Figure 2: see original paper]), with 89 nodes, 575 links, and density of 0.1468. China ranked first with 440 papers (24.9% of total), followed by the United States (404) and India (336). The UK showed the highest betweenness centrality (0.26), leading the field. Additionally, the US (0.18), India (0.17), China (0.13), Saudi Arabia (0.12), and Canada (0.11) also exhibited high centrality, with prominent purple rings around their nodes.

2.3 Institution Analysis

The institutional collaboration network map for AI in DR research (Figure 3 [Figure 3: see original paper]) included 436 nodes, 1,073 links, and density of 0.0113. Globally, 436 institutions conduct research in this field, with Sun Yat-sen University (47 papers), National University of Singapore (38), and Singapore National Eye Centre (34) ranking top three. Betweenness centrality was generally low across institutions, with Capital Medical University (0.10), Stanford University (0.09), and National University of Singapore (0.08) ranking highest. Among the top 15 institutions by publication volume, China had five: Sun Yat-sen University, Capital Medical University, Shanghai Jiao Tong University (28, 0.02), Chinese Academy of Sciences (25, 0.05), and Chinese University of Hong Kong (23, 0.03).

2.4 Author Analysis

CiteSpace generated an author collaboration network map (Figure 4 [Figure 4: see original paper]) with 601 nodes, 2,050 links, and density of 0.0114. JIA YALI and THOMAS HWANG tied for first with 21 papers each, followed by JIE WANG (20), ABRAMOFF MD (19), Hwang TS (18), WONG TY (18),

ACHARYA UR (17), AUGUSTINUS LAUDE (16), TING DSW (16), LIN HAOTIAN (15), and SIVAPRASAD SOBHA (15). Authors with $ $15 publications contributed 196 papers (11.1% of total). Figure 4 shows relatively weak and dispersed collaboration among researchers.

2.5.1 Author Co-Citation Analysis

Author co-citation analysis identified the top 10 cited authors (Table 1). GULSHAN V from Radboud University (412 citations), ABRAMOFF M from University of Iowa (363), and Ting D from National University of Singapore (285) ranked top three. Notably, ABRAMOFF M and Ting D appear in both high publication volume and high citation rankings, indicating significant contributions. ABRAMOFF M's co-citation centrality reached 0.17, substantially higher than others, demonstrating emphasis on literature quality and substantial influence.

Table 1 The top 10 cited authors for studies regarding artificial intelligence in diabetic retinopathy

Cited Author	Citation Frequency	Betweenness Centrality
GULSHAN V	412	-
ABRAMOFF M	363	0.17
TING D	285	-
NIEMEIJER M	-	-
QUELLEC G	-	-
GARGEYA R	-	-
SZEGEDY C	-	-
DECENCIERE E	-	-
KRIZHEVSKY A	-	-

2.5.2 Journal Co-Citation Analysis

Journal co-citation analysis identified the top 10 cited journals (Table 2), with eight ranked Q1 in Journal Citation Reports (JCR) and high impact factors (IF), indicating high-quality literature. *Ophthalmology* ranked first (IF: 14.277), followed by *Investigative Ophthalmology & Visual Science* (IF: 4.925) and *IEEE Transactions on Medical Imaging* (IF: 11.037). The first two are the most influential ophthalmology journals, while the third covers computer science and interdisciplinary applications.

Table 2 The top 10 cited journals for studies regarding artificial intelligence in diabetic retinopathy

Cited Journal	JCR Quartile	IF	Citation Frequency	Betweenness Centrality
OPHTHALMOLOGY	Q1	14.277	-	-
INVEST OPHTH VIS SCI	Q1	4.925	-	-
IEEE T MED IMAGING	Q1	11.037	-	-
BRIT J OPHTHALMOL	Q1	5.907	-	-
JAMA-J AM MED ASSOC	Q1	157.375	-	-
MED IMAGE ANAL	Q1	13.828	-	-
DIABETES CARE	Q1	17.155	-	-
PLOS ONE	Q2	3.752	-	-
AM J OPHTHALMOL	Q1	5.488	-	-
LECT NOTES COMPUT SC	-	-	-	-

2.5.3 Literature Co-Citation Analysis

Literature co-citation analysis identified the top 10 most-cited articles (Table 3). The most-cited article introduced a deep learning algorithm for automated detection of DR and diabetic macular edema (DME) in retinal fundus photographs [?]. The second most-cited explored a deep learning system' s performance in evaluating retinal images from multiethnic diabetic populations [?]. The third developed and evaluated a data-driven diagnostic tool for automated DR detection through fundus image processing [?]. These findings indicate extensive discussion of AI in DR screening and diagnosis, primarily focusing on fundus image analysis.

Table 3 The top 10 most-cited articles for studies regarding artificial intelligence in diabetic retinopathy

Title	Authors
Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs	Gulshan V et al.
Development and Validation of a Deep Learning System for Diabetic Retinopathy and Related Eye Diseases Using Retinal Images From Multiethnic Populations With Diabetes	Ting D et al.
Automated Identification of Diabetic Retinopathy Using Deep Learning	Gargeya R, Leng T
Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset Through Integration of Deep Learning	Abramoff M et al.
Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices	Abramoff M et al.
Deep learning	Lecun Y et al.
Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning	Kermany et al.
Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning	Poplin R et al.
Clinically applicable deep learning for diagnosis and referral in retinal disease	Grader et al.
Variability and the Importance of Reference Standards for Evaluating Machine Learning Models for Diabetic Retinopathy	Krause J et al.

2.6.1 Keyword Co-Occurrence Analysis

Keywords summarize paper themes, and co-occurrence analysis creates networks from keyword nodes and links [?]. Similar keywords were merged (e.g., "automated detection" & "automatic detection," "risk factor" & "risk," "retinal image" & "fundus image" & "retinal fundus image"). Based on publication growth trends, keyword evolution was analyzed in two phases: 2011–2017 and 2018–2022.

2.6.1.1 2011–2017: The keyword co-occurrence map (Figure 5 [Figure 5: see original paper]) contained 275 nodes, 449 links, and density of 0.0119. "Retinal image" appeared most frequently (148 times) beyond search terms. Top centrality keywords were macular edema (0.30), disease (0.21), and blood vessel (0.18). Research focused on AI-based DR screening, diagnosis, and classification, with automated detection, segmentation, diagnosis, optical coherence tomography, classification, system, and identification as mediating keywords.

2.6.1.2 2018–2022: The keyword co-occurrence map (Figure 6 [Figure 6: see original paper]) contained 414 nodes, 591 links, and density of 0.0069. Keyword quantity increased with higher frequency but weaker co-linearity. Deep learning (268 occurrences), validation, convolutional neural network, artificial intelligence, algorithm, prevalence, and risk factor showed dramatic frequency increases, particularly deep learning, indicating dominant DL research during this period. Compared to Figure 5, researchers intensified studies on AI algorithm performance and began exploring AI' s role in DR risk prediction.

2.6.2 Keyword Clustering Analysis

Based on keyword co-occurrence, clustering analysis yielded a map with Q=0.7952 and S=0.9114 (Figure 7 [Figure 7: see original paper]). Smaller cluster numbers indicate larger scale and more keywords [?]. Twenty-six clusters were identified; the top 10 were deep learning, optical coherence tomography angiography, support vector machine, retinal fundus images, diabetes mellitus, image analysis, disease, management, diabetic macular edema, and image segmentation. Analysis reveals research hotspots concentrated on DR lesion segmentation and AI-based fundus image diagnosis.

2.6.3 Keyword Burst Analysis

Keyword burst analysis detects high-frequency, rapidly growing keywords to identify attention-grabbing research and trends [?]. "Begin" indicates burst start time, "end" indicates finish, and "strength" represents burst intensity. The burst map (Figure 8 [Figure 8: see original paper]) detected 20 burst keywords, all first appearing in 2011, sorted by burst start time. Currently influential bursts include automated detection (strength 12), segmentation (11.84), and extraction (9.86). Long-duration bursts include red lesion (2011–2018), automated detection (2011–2017), segmentation (2011–2017), retinopathy (2011–2017), mathematical morphology (2012–2018), and lesion (2012–2018). Automated detection showed the highest burst strength and long duration, confirming its status as a recent research hotspot.

Discussion

3.1 Analysis of Publications, Countries, Institutions, Authors, and Cited Journals

Results show rising publication volume in AI applications for DR, with trends predicting continued growth. Country collaboration analysis indicates China leads in publication volume, while the UK, despite ranking fourth, shows highest betweenness centrality and substantial international influence. The US and India rank high in both volume and centrality, representing important research hubs. Institutional collaboration networks reveal generally low betweenness centrality, requiring enhanced influence and closer inter-institutional cooperation —limitations that restrict field development. Among the top 15 institutions by publication volume, China has five, demonstrating extensive research activity and numerous authoritative institutions. Author collaboration networks show low overall density, indicating weak exchange and cooperation. This suggests future efforts should strengthen collaboration across regions and institutions while deepening research. Author co-citation analysis shows GULSHAN V, ABRAMOFF M, and Ting D made significant contributions with high academic status. Journal co-citation analysis identifies *Ophthalmology*, *Investigative Ophthalmology & Visual Science*, and *IEEE Transactions on Medical Imaging* as highly cited and influential, likely to publish more AI-DR research in the future.

3.2 Research Hotspots in AI Applications for DR

Based on co-citation, keyword co-occurrence, and clustering results, AI research in DR primarily centers on lesion segmentation and diagnosis.

3.2.1 Lesion Segmentation Lesion segmentation is the core step in AI disease diagnosis. Separating key lesions from images and extracting features forms the basis for subsequent diagnosis, treatment, and efficacy evaluation [?]. DR pathological features include microaneurysms, exudates, vascular abnormalities, and hemorrhages [?].

Microaneurysms (MAs) are among the earliest visual signs of DR, attracting extensive research interest [?]. However, low contrast and sparse pixel distribution in fundus images make detection challenging. Xia et al. [?] proposed a multi-scale segmentation-classification model improving MAs detection accuracy in complex cases. Liao et al. [?] designed a novel deep convolutional encoder-decoder network for precise MAs localization and efficient detection, reducing test time while maintaining performance. Zhang et al. [?] introduced a feature-transfer network with local background suppression to measure differences between background noise and retinal targets, addressing data imbalance.

Exudates represent another important DR biomarker, with extensive research on segmentation. Huang et al. [?] proposed an automatic exudate detection method combining superpixel multi-feature extraction and patch-based CNN. Kurilova et al. [?] combined support vector machine (SVM) classifiers with faster R-CNN object detectors for hard exudate identification, using SVM pre-scanning to improve and accelerate detection under limited training data. Mohan et al. [?] developed an improved KAZE feature-based method addressing issues of varying exudate size, irregular illumination, and poor contrast.

Retinal vessel segmentation is crucial for DR diagnosis, involving geometric features like branch length, angle, and diameter. Tian et al. [?] proposed a multi-path CNN method effectively suppressing noise while ensuring vessel continuity. Atli et al. [?] introduced a fully automatic DL architecture overcoming pathologies, noise, and poor contrast, showing clinical potential. Gegundez-Arias et al. [?] developed a U-Net-based CNN method considering pixel distance to vascular trees, generating pixel-level probability maps for vessel segmentation.

Retinal hemorrhage, formed by ruptured vessels under extreme pressure, is another research focus [?]. Maqsood et al. [?] first enhanced edge details through improved contrast enhancement, then applied a novel CNN structure for hemorrhage detection and feature fusion, achieving excellent visual and quantitative performance. Lahmiri et al. [?] proposed a three-stage hybrid system using CNN for automatic feature extraction, optimal feature selection, and optimized non-linear SVM classification, demonstrating superior speed and accuracy compared to three reference systems.

DR lesion feature recognition is critical for early screening, diagnosis, treatment, and follow-up. While traditionally performed by trained experts, manual diagnosis is cumbersome, error-prone, and resource-intensive. AI can rapidly segment lesions and precisely extract unique features at each DR stage, promising efficient, scalable, sustainable, and cost-effective new models [?].

3.2.2 AI Application in DR Diagnosis DR is often asymptomatic in early stages, with many patients presenting only after vision loss becomes irreversible [?]. Thus, early diagnosis is crucial for preventing vision impairment. Fundus photography is the most cost-effective DR examination, driving abundant research on AI-based DR diagnosis from fundus images. Li et al. [?] developed an ensemble DR diagnostic model using fundus images, investigating input size and quantity effects on performance, ultimately demonstrating good generalization. Fundus images often suffer from chromatic aberrations and irrelevant lighting, reducing diagnostic quality. Kaushik et al. [?] addressed this using image desaturation preprocessing and stacked three CNNs for DR classification, achieving superior results. While existing grading methods typically train on high-resolution images, clinical practice more commonly uses low-resolution images, substantially reducing performance. Wang et al. [?] proposed a network focusing on low-resolution images, jointly performing super-resolution, lesion segmentation, and DR grading using CNN-based methods, outperforming other methods across three datasets. Shankar et al. [?] established a DL-based automatic DR detection model with denoising preprocessing, achieving satisfactory results on the Messidor DR dataset.

With continuous research advancement, multiple DR diagnostic systems have emerged. Since the FDA approved the first AI system for DR diagnosis (IDx-DR) in 2018 [?], EyeArt [?] and Retmarker DR [?] have also gained approval. Additionally, Shenzhen Sibionics' AI-based DR screening software and Airdoc' s AI-based DR analysis software were approved in August 2020 [?], marking clinical acceptance and growing adoption of AI in DR diagnosis.

3.3 Research Trends in AI Applications for DR

Keyword burst analysis suggests trends in automated detection, including DME efficacy prediction, DR disease management, and AI algorithm performance improvement.

DME, characterized by blood-retinal barrier disruption and macular fluid accumulation [?], is the primary cause of vision loss in DR patients. Anti-vascular endothelial growth factor (VEGF) therapy is the first-line treatment but is not universally effective, with some patients showing poor response. Predicting treatment response can avoid unnecessary trial-and-error and facilitate more effective therapy selection. Allingham et al. [?] used semi-automated fluorescein angiography segmentation to compare anti-VEGF effects on MAs-related versus non-MAs-related leakage, suggesting the latter as a VEGF-mediated pathology marker and that MAs-predominant patients may respond poorly. Rasti et al. [?] proposed an OCT image-based method for predicting anti-VEGF treatment efficacy, using pre-treatment scans as input and retinal thickness difference as output, achieving 0.866 AUC, 85.5% precision, 80.1% sensitivity, and 85.0% specificity through 5-fold cross-validation. AI is transforming DR diagnosis and treatment workflows.

As AI applications in DR diagnosis and treatment expand, its potential in disease management has attracted attention. Estil et al. [?] implemented a DR risk algorithm in Norwegian ophthalmology clinics using individual risk profiles (gender, diabetes type, DR severity, duration, HbA1c, blood pressure) to estimate vision-threatening DR risk and personalize screening intervals, reducing clinic visits and saving resources. Bora et al. [?] developed two DL systems based on Inception-V3 to predict DR development in patients undergoing tele-DR screening in primary care, optimizing screening intervals to reduce costs while improving vision outcomes. Xie et al. [?] developed an AI algorithm to detect drug-induced retinal changes in diabetic animal models through HE pathology sections, identifying ganglion cell and nerve fiber layer changes for early diagnosis and drug efficacy evaluation, proposing a novel quantitative screening method.

With deepening research, diverse data types are being integrated to improve AI model performance. Torok et al. [?] developed a combined tear proteomics and fundus image AI system for DR detection, demonstrating higher sensitivity and specificity than either modality alone, suggesting complementary benefits. Multimodal data combination analysis using DL shows significant advantages and represents an emerging trend in DR AI research.

Numerous studies demonstrate AI systems' irreplaceable efficiency and potential value as DR diagnostic aids [?]. From model development and validation to clinical translation, performance improvement, and socioeconomic value assessment, these studies mark AI' s maturation in DR. However, challenges remain: (1) The black-box problem [?] has become critical as AI applications expand. (2) Dataset quality and quantity: AI algorithms require precise training, testing, and validation datasets; unrepresentative or small datasets yield inaccurate results. Additionally, equipment, patient cooperation, and physician skill affect data collection, hindering standardized large database establishment [?]. (3) Ethical issues: AI in healthcare doesn' t inherently prioritize "patient benefit maximization," complicating doctor-patient relationships. Protecting patient data privacy while advancing AI and determining liability for AI errors in ophthalmology require resolution. Future research must focus on algorithm improvement, standardized quality control processes, high-quality database platforms, and ethical guidelines.

Conclusion and Limitations

This study used CiteSpace to visually analyze DR AI application literature from WOS, exploring research status, hotspots, and trends, clearly presenting recent achievements and analyzing advantages and challenges to provide references for future research. Limitations include missing other databases and potential sample omission, leading to incomplete data collection and biased visualization. Future studies should expand database coverage for more comprehensive and objective field representation.

Author Contributions

Liu Chun: conceptualization, study design, implementation, results analysis and interpretation, manuscript writing and revision. Jian Wenyuan: chart preparation, data collection and organization. Duan Junguo: final manuscript revision, quality control and review, overall responsibility.

Conflict of Interest Statement

The authors declare no conflict of interest.

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Note: Figure translations are in progress. See original paper for figures.