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Research article

# Global research of artificial intelligence in eyelid diseases: A bibliometric analysis

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A R T I C L E I N F O

*Keywords:*
Artificial intelligence
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Global publications

A B S T R A C T

*Purpose:* To generate an overview of global research on artificial intelligence (AI) in eyelid diseases using a bibliometric approach.
*Methods:* All publications related to AI in eyelid diseases from 1900 to 2023 were retrieved from the Web of Science (WoS) Core Collection database. After manual screening, 98 publications published between 2000 and 2023 were finally included. We analyzed the annual trend of publication and citation count, productivity and co-authorship of countries/territories and institutions, research domain, source journal, co-occurrence and evolution of the keywords and co-citation and clustering of the references, using the analytic tool of the WoS, VOSviewer, Word-cloud Python package and CiteSpace.
*Results:* By analyzing a total of 98 relevant publications, we detected that this field had continuously developed over the past two decades and had entered a phase of rapid development in the last three years. Among these countries/territories and institutions contributing to this field, China was the most productive country and had the most institutions with high productivity, while USA was the most active in collaborating with others. The most popular research domains was Ophthalmology and the most productive journals were Ocular Surface. The co-occurrence network of keywords could be classified into 3 clusters respectively concerned about blepharoptosis, meibomian gland dysfunction and blepharospasm. The evolution of research hotspots is from clinical features to clinical scenarios and from image processing to deep learning. In the clustering analysis of co-cited reference network, cluster "0# deep learning" was the largest and latest, and cluster "#5 meibomian glands visibility assessment" existed for the longest time.
*Conclusions:* Although the research of AI in eyelid diseases has rapidly developed in the last three years, there are still gaps in this area. Our findings provide researchers with a better understanding of the development of the field and a reference for future research directions.

## 1. Introduction

Eyelid pathologies, including inflammation, positional and functional abnormalities and tumors, are common presentations in

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ophthalmology clinics [1]. Since the eyelid is an important barrier that protects the eye and closely connects with conjunctiva, cornea and tear film in the ocular surface system [2], eyelid diseases can cause irritative symptoms, corneal lesions, eye deformities and even vision loss [1]. Therefore, eyelid diseases need to be diagnosed and intervened in the early stages. With the advancement of medical technology, imaging data (such as meibography and external ocular photographs) play an increasingly important role in the diagnosis and treatment of eyelid diseases [3,4]. However, manual analysis of these images is inefficient and error-prone. Moreover, considering the present and future limitations with access to ophthalmology specialists, there is an urgent need for automated technology to assist in clinical work [5].

Artificial intelligence (AI) is about using computers to simulate and extend intelligent behavior with minimal human intervention, which has been widely used in medicine in recent years [6]. Benefiting from the abundant image data, ophthalmology was one of the first specialties focusing on the AI application [7]. Although eyelid diseases are newly researched diseases in this field in contrast to diabetic retinopathy and other eye diseases [8], some studies have attempted to apply AI to assist the diagnosis, treatment and prognosis of eyelid diseases [9–11]. In view of the development of the research on AI in eyelid diseases, it is necessary to analyze the trends and research patterns of it. However, there is no bibliometric analysis on this topic yet.

Bibliometric analysis is a method of exploring and analyzing large amounts of scientific data, which can reflect the importance of publications and interactions among scholars in a research field and provide a preview of the future through different techniques for science mapping, such as citation analysis, co-word analysis, and co-authorship analysis [12]. The use of bibliometric analysis in analyzing the research on AI in ophthalmology is widespread, including macular edema, glaucoma and strabismus [13–15]. Therefore, this study was aimed to conduct a comprehensive analysis of the research on AI in eyelid diseases for the purpose of providing an overview as well as forecast of this research field.

## 2. Material and methods

### *2.1. Data search strategy*

Based on the recommendation of collecting bibliometric data from single database [12], all data included in this study were extracted from the Web of Science (WoS) Core Collection, the most frequently used and recognized database for bibliometric research [16]. The literature search was conducted using a retrieval formula composed of a series of keywords related to AI and a series of keywords related to eyelid diseases, which was as follows: TS = ("eyelid margin*" OR "lid margin*" OR "eyelid fissure*" OR "lid fissure*" OR "palpebral fissure*" OR "orbicularis oculi muscle*" OR "levator palpebrae" OR "meibomian gland*" OR "eyelid disease*" OR "eyelid lesion*" OR hordeolum OR meibomitis OR chalazion OR blepharitis OR "eyelid tumor*" OR "hemangioma of the lid" OR "nevus of the lid" OR "xanthelasma of the lid" OR "eyelid basal cell carcinoma" OR "eyelid sebaceous gland carcinoma" OR "eyelid squamous cell carcinoma" OR trichiasis OR "aberrant lashes" OR entropion OR ectropion OR lagophthalmus OR ptosis OR blepharoptosis OR epicanthus OR blepharophimosis OR blepharospasm OR "meibomian gland dysfunction" OR "eyelid injury") AND TS = ("artificial intelligence" OR AI OR "machine learning" OR "supervised learning" OR "semi-supervised learning" OR "unsupervised learning" OR "deep learning" OR "neural network" OR "computer vision" OR "image processing" OR "image segmentation" OR "feature detection" OR "fast fourier transform" OR "K-means" OR "C-means" OR "support vector machine" OR automat*). The literature types included articles, proceeding papers, review articles and early access. The timespan was from 1900 to 2023. The final search was conducted when the data of WoS Core Collection was updated to December 31, 2023. A total of 285 publications were retrieved for following screening.

### *2.2. Data screening strategy*

To ensure publications included for the bibliometric analysis were relevant to AI and eyelid diseases, the manual review was independently executed by two authors (XZ and ZZ), and included studies on: (i) eyelid diseases; (ii) clinically useful AI approaches about eyelid diseases, such as the approach to segment meibomian glands using near-infrared images and the approach to segment palpebral fissures from eye videography. With scrutiny of the title, abstract and keywords, 98 publications were finally included in the bibliometric analysis.

### *2.3. Data analysis and visualization*

The statistics on publications, including citations, Hirsch-index (H-index), countries/territories, institutions, research domains and journals were extracted from the analytic tool of the WoS. The H-index, denoting that h publications of an author have at least h citations each, is a synthetic assessment of both quantity and quality, which was used to measure the scientific impact of a scientist and is now also extensively used to evaluate the academic productivity and impact of journals, countries/territories and institutions [17,18]. The Journal Impact Factor and Rank of journals which can reflect the academic influence were extracted from the Journal Citation Reports 2023 published on June 28, 2023. Microsoft Excel 2016 was used to generate charts and tables for presenting the results. The full record and cited references of the included publications were exported to plain text file from the WoS and were imported into VOSviewer (version 1.6.17) and CiteSpace 6.3. R3 to visualize the co-authorship of countries/territories and institutions, the co-occurrence of author keywords and the co-citation and clustering of reference. For a better presentation, thesaurus file were imported into VOSviewer and meaningless words were excluded when generating the keywords map. Wordcloud Python package were applied to generate word cloud maps for finding research hotspots, using the data of titles, abstracts and keywords which were exported from WoS. Word cloud maps were divided into three files by publication year. Synonym and insignificant words were likewise excluded from the word cloud maps.

## 3. Results

### 3.1. Analysis of annual publications and citations

After searching and screening, we analyzed 98 publications on AI and eyelid diseases that were published between 2000 and 2023, including 86 journal articles, 9 proceedings and 3 reviews. The annual trends of publications and citations were displayed in Fig. 1. Before 2017, there were only a few studies about AI and eyelid diseases. From 2017 to 2020, the research of AI applied to eyelid diseases slowly evolved, with an increase in the annual number of publications. The rapid development of the research on application of AI in eyelid diseases began in 2021 and the number of publications in the last three years was 69.39 % (68/98) of all publications included in this study. Similarly, the number of citations sharply increased since 2017.

Table 1 showed the top 10 publications in the ranking of annual citation count, of which all were journal articles and 80 % (8/10) were published between 2019 and 2022. The article by Koh et al. in 2012 was the earliest, which presented a method to automatically measure the width and length of meibomian glands in infrared meibography images and classify these images [19]. The article by Arita et al. in 2014, introducing a software for automatic and objective measurement of meibomian gland area in meibography images and comparing the results of the software with subjective grading, was the most influential [20]. Table 1 also showed the top 10 publications in the ranking of total citation count. By comparison with the list of annual citation count, although the earliest article and the most influential article on this list was the same as above, 2 articles published in 2016, 1 articles published in 2017 took the place of these articles published in the last three years.

### 3.2. Analysis of countries/territories and institutions

In all, 24 countries/territories and 211 institutions contributed to the research on AI applied to eyelid diseases. Table 2 listed the top 10 countries in the ranking of publication count and citation count. With the most publications (44/98, 44.90 %) and total 219 citations, China was the most productive countries, followed by USA (17/98, 17.35 %, 140 citations). It is noteworthy that Japan ranked 5th on this list (5/98, 5.10 %, 104 citations) while it ranked 1st by average citation count per publication (20.8 citations per publication). Table 2 also listed the top 10 institutions in the ranking of publication count and citation count, excluding some institutions which have inclusive relationship with other institutions, such as University of California System (including University of California Berkeley and others), International Computer Science Institute (affiliating to University of California Berkeley). The most fruitful institution was Wenzhou Medical University (10/98, 10.20 %), followed by Zhejiang University (8/98, 8.16 %). With the least publications (3/98, 3.06 %) among the top 10 institutions, University of California Berkeley ranked 1st by average citation count per publication (17 citations per publication). In addition, Chinese institutions accounted for 60 % (6/10) of the top 10 institutions.

The collaboration networks among countries/territories and institutions were shown in Fig. 2. Among 13 countries/territories with cooperative relationships, USA had the highest total strength of the co-authorship links with 9 other countries/territories, followed by China and South Korea cooperating with 6 other countries/territories (Table S1). Regarding 59 institutions with cooperative relationships, the total strength of the co-authorship links of Wenzhou Medical University with 17 other institutions was the highest, followed by Zhejiang University cooperating with 15 other institutions (Table S2).

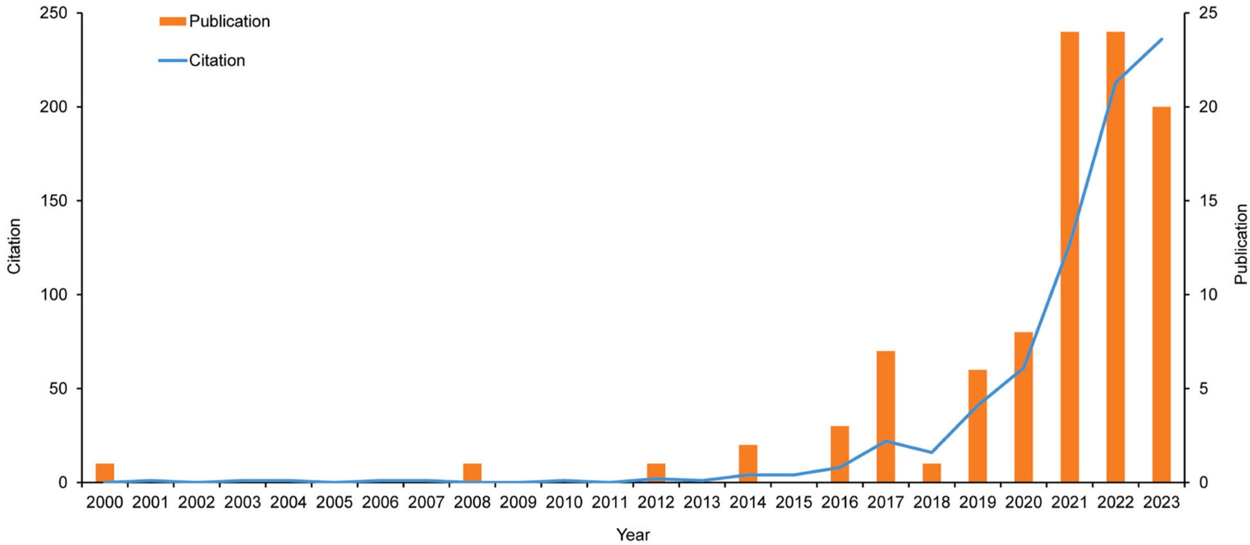


**Fig. 1.** Trends of publications and citations of artificial intelligence in eyelid diseases.

**Table 1**
Top publications in the ranking of annual citation count and total citation count.

| References | Title | Year | C/Y | Source Title |
|---|---|---|---|---|
| Arita et al. [20] | Objective image analysis of the meibomian gland area | 2014 | 7.36 | Br J Ophthalmol |
| Song et al. [10] | A clinical decision model based on machine learning for ptosis | 2021 | 5.5 | BMC Ophthalmol |
| Xiao et al. [21] | An automated and multiparametric algorithm for objective analysis of meibography images | 2021 | 4.75 | Quant Imaging Med Surg |
| Wang et al. [22] | A Deep Learning Approach for Meibomian Gland Atrophy Evaluation in Meibography Images | 2019 | 4.67 | Transl Vis Sci Technol |
| Koh et al. [19] | Detection of meibomian glands and classification of meibography images | 2012 | 4.38 | J Biomed Opt |
| Maruoka et al. [23] | Deep Neural Network-Based Method for Detecting Obstructive Meibomian Gland Dysfunction With in Vivo Laser Confocal Microscopy | 2020 | 4.2 | Cornea |
| Prabhu et al. [24] | Deep learning segmentation and quantification of Meibomian glands | 2020 | 4.2 | Biomed Signal Process Control |
| Llorens-Quintana et al. [25] | A Novel Automated Approach for Infrared-Based Assessment of Meibomian Gland Morphology | 2019 | 3.67 | Transl Vis Sci Technol |
| Zhang et al. [26] | Meibomian Gland Density: An Effective Evaluation Index of Meibomian Gland Dysfunction Based on Deep Learning and Transfer Learning | 2022 | 3.67 | J Clin Med |
| Li et al. [27] | Artificial intelligence to detect malignant eyelid tumors from photographic images | 2022 | 3.67 | NPJ Digit Med |
| **References** | **Title** | **Year** | **TC** | **Source Title** |
| Arita et al. [20] | Objective image analysis of the meibomian gland area | 2014 | 81 | Br J Ophthalmol |
| Koh et al. [19] | Detection of meibomian glands and classification of meibography images | 2012 | 57 | J Biomed Opt |
| Wang et al. [22] | A Deep Learning Approach for Meibomian Gland Atrophy Evaluation in Meibography Images | 2019 | 28 | Transl Vis Sci Technol |
| Koprowski et al. [28] | A quantitative method for assessing the quality of meibomian glands | 2016 | 25 | Comput Biol Med |
| Bodnar et al. [29] | Automated Ptosis Measurements From Facial Photographs | 2016 | 23 | JAMA Ophthalmol |
| Song et al. [10] | A clinical decision model based on machine learning for ptosis | 2021 | 22 | BMC Ophthalmol |
| Llorens-Quintana et al. [25] | A Novel Automated Approach for Infrared-Based Assessment of Meibomian Gland Morphology | 2019 | 22 | Transl Vis Sci Technol |
| Maruoka et al. [23] | Deep Neural Network-Based Method for Detecting Obstructive Meibomian Gland Dysfunction With in Vivo Laser Confocal Microscopy | 2020 | 21 | Cornea |
| Prabhu et al. [24] | Deep learning segmentation and quantification of Meibomian glands | 2020 | 21 | Biomed Signal Process Control |
| Koprowski et al. [30] | A clinical utility assessment of the automatic measurement method of the quality of Meibomian glands | 2017 | 21 | Biomed Eng Online |

C/Y: average citation count per year; TC: total citation count.

**Table 2**
Top countries and institutions in the ranking of publications count and citation count.

| Country/Territory | Publications | % of publications | Citations | Average citation per publication | H-index |
|---|---|---|---|---|---|
| China | 44 | 44.90 % | 219 | 4.98 | 10 |
| USA | 17 | 17.35 % | 140 | 8.24 | 8 |
| UK | 10 | 10.20 % | 31 | 3.1 | 4 |
| South Korea | 8 | 8.16 % | 48 | 6 | 3 |
| Japan | 5 | 5.10 % | 104 | 20.8 | 2 |
| Poland | 5 | 5.10 % | 78 | 15.6 | 4 |
| Spin | 4 | 4.08 % | 32 | 8 | 2 |
| Italy | 4 | 4.08 % | 23 | 5.75 | 2 |
| Brazil | 3 | 3.06 % | 17 | 5.67 | 2 |
| Germany | 3 | 3.06 % | 17 | 5.67 | 2 |
| **Institution (Country)** | **Publications** | **% of publications** | **Citations** | **Average citation per publication** | **H-index** |
| Wenzhou Medical University (China) | 10 | 10.20 % | 43 | 4.3 | 4 |
| Zhejiang University (China) | 8 | 8.16 % | 44 | 5.5 | 4 |
| University of London (UK) | 7 | 7.14 % | 24 | 3.43 | 3 |
| Shanghai Jiao Tong University (China) | 6 | 6.12 % | 52 | 8.67 | 4 |
| Capital Medical University (China) | 5 | 5.10 % | 25 | 5 | 2 |
| Sun Yat-sen University (China) | 4 | 4.08 % | 41 | 10.25 | 3 |
| Communication University of Zhejiang (China) | 4 | 4.08 % | 11 | 2.75 | 1 |
| Queen Mary University of London (England) | 4 | 4.08 % | 11 | 2.75 | 1 |
| University of California Berkeley (USA) | 3 | 3.06 % | 51 | 17 | 3 |
| Gwangju Institute of Science and Technology (South Korea) | 3 | 3.06 % | 26 | 8.67 | 2 |

H-index: Hirsch-index.

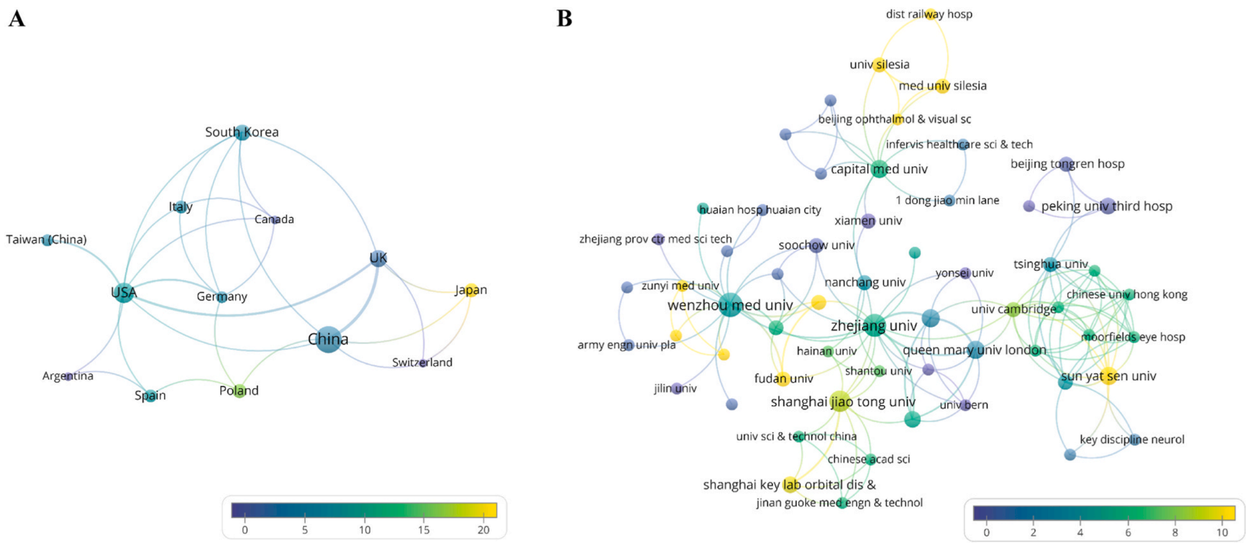


**Fig. 2.** Collaboration between countries/territories and institutions. (A) The co-authorship network of countries/territories. (B) The co-authorship network of institutions. Circle size represents the number of publications; circle color represents average citation per publication; links represent the collaboration. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

### *3.3. Analysis of research domains and journals*

According to WoS categories, the publications included in this study belonged to 37 research domains. Table 3 demonstrated the top 10 research domains in the ranking of publication count and citation count. The most popular research domains of research on AI applied to eyelid diseases was Ophthalmology (31/98, 31.63 %, 338 citations), followed by Engineering Biomedical (12/98, 12.24 %, 126 citations).

Table 4 demonstrated the top 10 journals in the ranking of publication count and citation count. With the most publications (5/98, 5.10 %), Ocular Surface was the most prolific journal, followed by Frontiers in Cell and Developmental Biology (4/98, 4.08 %). It is also remarkable that Translational Vision Science & Technology ranked 1st by citation count (61 citations) and Biomedical Engineering Online ranked 1st by average citation count per publication (20.5 citations per publication) among these 10 journals. Moreover, in the light of Journal Citation Reports 2023, Table 5 showed the top 10 journals in the ranking of the Journal Impact Factor, which all ranked Q1. Nature Medicine was the journal with the highest JIF (JIF = 82.9), publishing a study about a new technology based on three-dimensional reconstruction and deep learning algorithms for protecting the privacy of patients' facial images when diagnosing eyelid diseases [31]. It was followed by NPJ Digital Medicine (JIF = 15.2), which published a highly cited article on a convolutional neural network and classification network-based automatic system to detect malignant eyelid tumors (3.67 citations per year, ranked 10th in Table 1) [27].

### *3.4. Analysis of keywords*

In order to deepen the understanding of the research hotspots of AI applied to eyelid diseases and the connections between them, Fig. 3 visually displayed the results of co-occurrence analysis and cluster analysis of keywords. Among the 224 keywords recognized by VOSviewer in accordance with the thesaurus file, 49 keywords appeared at least twice and were sorted into 3 clusters with different

**Table 3**
The most related research domains in the ranking of publication count and citation count.

| Research Domain (Wos categories) | Publications | % of publications | Citations | Average citation per publication |
|---|---|---|---|---|
| Ophthalmology | 31 | 31.63 % | 338 | 10.9 |
| Engineering Biomedical | 12 | 12.24 % | 126 | 10.5 |
| Medicine General Internal | 8 | 8.16 % | 46 | 5.75 |
| Engineering Electrical Electronic | 8 | 8.16 % | 22 | 2.75 |
| Computer Science Artificial Intelligence | 8 | 8.16 % | 10 | 1.25 |
| Computer Science Interdisciplinary Applications | 7 | 7.14 % | 41 | 5.86 |
| Medical Informatics | 7 | 7.14 % | 40 | 5.71 |
| Computer Science Information Systems | 7 | 7.14 % | 25 | 3.57 |
| Neurosciences | 6 | 6.12 % | 19 | 3.17 |
| Health Care Sciences Services | 5 | 5.10 % | 29 | 5.8 |

Some publications belong to multiple research domains.

**Table 4**
The most productive journals in the ranking of publication count and citation count.

| Source Title | Publications | % of publications | Citations | Average citation per publication | H-index |
|---|---|---|---|---|---|
| Ocular Surface | 5 | 5.10% | 33 | 6.6 | 4 |
| Frontiers in Cell and Developmental Biology | 4 | 4.08% | 4 | 1 | 1 |
| Translational Vision Science & Technology | 3 | 3.06% | 61 | 20.33 | 3 |
| Biomedical Signal Processing and Control | 3 | 3.06% | 26 | 8.67 | 2 |
| Graefes Archive for Clinical and Experimental Ophthalmology | 3 | 3.06% | 21 | 7 | 2 |
| Scientific Reports | 3 | 3.06% | 15 | 5 | 1 |
| Journal of Clinical Medicine | 3 | 3.06% | 11 | 3.67 | 1 |
| Biomedical Engineering Online | 2 | 2.04% | 41 | 20.5 | 2 |
| Computers in Biology and Medicine | 2 | 2.04% | 31 | 15.5 | 2 |
| Cornea | 2 | 2.04% | 27 | 13.5 | 2 |

H-index: Hirsch-index.

**Table 5**
The most influential journals in the ranking of Journal Impact Factor reported in 2023.

| Source Title | Journal Citation Reports 2023 | | Publications | % of publications | Citations | Average citation per publication |
|---|---|---|---|---|---|---|
| | Journal Impact Factor | Rank | | | | |
| Nature Medicine | 82.9 | Q1 | 1 | 1.02 % | 6 | 6 |
| NPJ Digital Medicine | 15.2 | Q1 | 1 | 1.02 % | 11 | 11 |
| EClinicalMedicine | 15.1 | Q1 | 1 | 1.02 % | 14 | 14 |
| Annals of Neurology | 11.2 | Q1 | 1 | 1.02 % | 1 | 1 |
| Expert Systems with Applications | 8.5 | Q1 | 1 | 1.02 % | 0 | 0 |
| JAMA Ophthalmology | 8.1 | Q1 | 1 | 1.02 % | 23 | 23 |
| Journal of Big Data | 8.1 | Q1 | 1 | 1.02 % | 2 | 2 |
| Computers in Biology and Medicine | 7.7 | Q1 | 2 | 2.04 % | 31 | 15.5 |
| IEEE Journal of Biomedical And Health Informatics | 7.7 | Q1 | 1 | 1.02 % | 2 | 2 |
| Ocular Surface | 6.4 | Q1 | 5 | 5.10 % | 33 | 6.6 |

Journal Citation Reports 2023 was published on June 28, 2023.

colors; 24 keywords in red were about clinical features of blepharoptosis and AI applied to it, such as “margin reflex distance”, “palpebral fissures”, “convolutional neural network” and “image segmentation”; 14 keywords in green were about clinical features of meibomian gland dysfunction and AI applied to it, such as “mebomain gland”, “infrared meibography”, “pattern recognition” and “spatial attention”; 11 keywords in blue were about clinical features of blepharospasm and AI applied to it, such as “blepharospasm rating scale”, “resting-state functional magnetic resonance imaging”, “machine learning” and “support vector machine”.

Furthermore, the publications included in this study were separated into 3 stages by publication year to explore the evolution process and development direction of research hotspots of AI applied to eyelid diseases: (i) 2000–2016; (ii) 2017–2020; (iii) 2021–2023. Fig. 4 displayed the word cloud maps generated in terms of the documents containing the title, abstract and keywords of these publications. The frequency of occurrence was indicated by the size of the word. The more times a word occurs, the bigger the word appears in the word cloud maps. During the entire period, “eyelid” and “meibomian gland” were always ranking the top 3 in regard of the frequency of occurrence. From 2000 to 2016, “eyelid measurement”, “margin reflex distance”, “meibography”, “automatic” and “image processing” were frequently occurring keywords. From 2017 to 2020, “automated analysis”, “meibomian gland dysfunction”, “manual measurement”, “blepharospasm” and “eyelid measurement” were frequently occurring keywords. From 2021 to 2023, “model performance”, “deep learning”, “image segmentation”, “meibography” and “automated analysis” were frequently occurring keywords.

### *3.5. Analysis of reference*

In order to explore the intellectual structure of AI applied to eyelid diseases, Fig. 5 visualize the results of co-citation analysis and cluster analysis of references. In this co-cited references network with 265 reference nodes and 657 co-citation links constructed by CiteSpace, the node size indicated the citation count of the reference, and the thickness of the purple ring represented the extent of the betweenness centrality, and the nodes at the end of the bolded links have high degree centrality. They were all used to measure the importance of the reference. The references with more citations and higher betweenness centrality were labelled in Fig. 5A. The most cited reference was an article by Wang et al. in 2019, which introduced a deep learning approach for automatic segmentation of eyelids and meibomian gland atrophy regions and computation of percent atrophy [22]. The reference with the highest betweenness centrality was a review by Baudouin et al. in 2016, focusing on the pathophysiology of meibomian gland dysfunction [32], followed by an article by Esteva et al. in 2017, which introduced an approach using deep neural networks for automatic classification of skin lesions [33]. It is

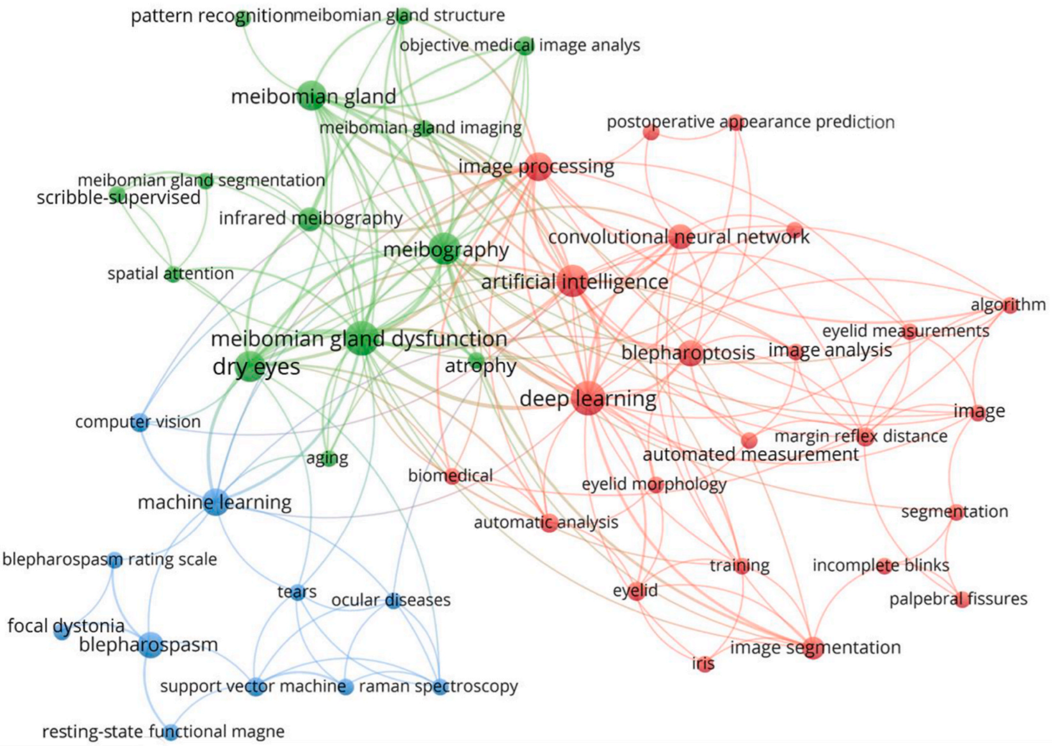


**Fig. 3.** The co-occurrence network of keywords classified in 3 clusters. Circle size represents the frequency of occurrence; links represent the co-occurrence; circles in the same color belong to a cluster. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

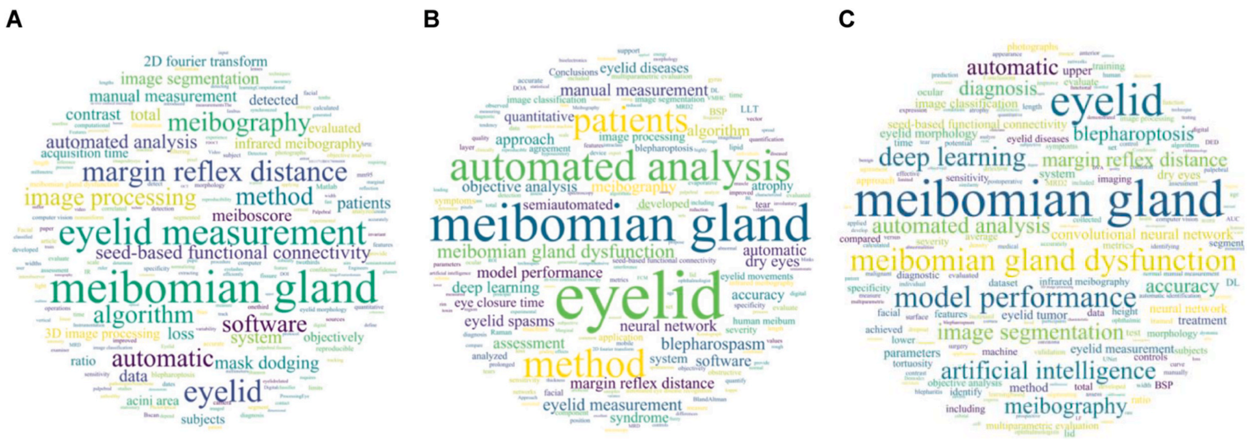


**Fig. 4.** Cloud maps of keywords during different periods. (A) 2000–2016; (B) 2017–2020; (C) 2021–2023. Font size represents the frequency of occurrence.

obvious that these two references also had high degree centrality and they were the hub points in this network [34]. The Modularity Q score and Weighted Mean Silhouette score were used to evaluate the rationality of the division of the network and the homogeneity of the clusters, and higher Q scores and closer silhouette score to 1 indicated better clustering [35]. Fig. 5B showed the co-cited references network with 9 major clusters, of which the Modularity Q = 0.8289 and Weighted Mean Silhouette S = 0.9324. The clusters were labelled in order of their size, and the largest cluster was marked as “#0 deep learning”. As cluster labelled 4#, 8# and 10# were discrete from other clusters, they were not shown in Fig. 5B.

Fig. 6 displayed the timeline map of the 9 major clusters and the cluster dependencies of reference. Among these major clusters in Fig. 6A, the earliest cluster “#1 meibomian gland area” appeared in 2008, while the latest clusters “#0 deep learning” and “#3 noninvasive identification” appeared in 2017. With the longest time span, the cluster “#5 meibomian glands visibility assessment”

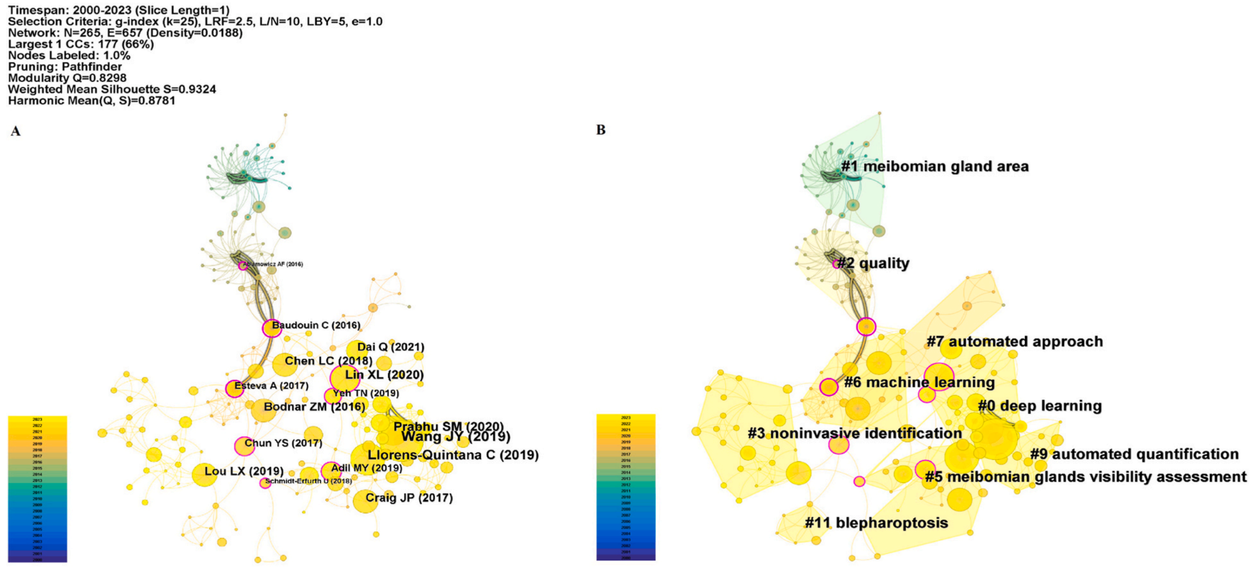


**Fig. 5. The network of co-cited references.** (A) References with more citations and higher betweenness centrality; (B) Major clusters visualization.

appeared in 2015. Fig. 6B used the arrows to indicate that the references of the cluster in the head of the arrow were cited by the references of the cluster in the tail. The cluster "#0 deep learning" was the center, combining the knowledge from other four clusters, while the cluster "#5 meibomian glands visibility assessment" fused the knowledge from two clusters and branched them to the other two clusters.

## 4. Discussion

In this study, we conducted a comprehensive analysis of the research on AI in eyelid diseases with publications extracted from the WoS Core Collection and uncovered the general trend, countries/territories and institutions involved, main domain, targeted source and research hotspots.

Since the first research on AI applied to eyelid diseases was published in 2000, this field has continuously developed and gained more and more attention over the past two decades with increasing publications and citations. By analyzing the annual trends of the publications and citations, the development history of research on AI in eyelid diseases could be divided into a nascent stage (2000–2016), a slow development stage (2017–2020) and a rapid development stage (2021–2023). It may be explained by the breakthroughs in the application of AI, such as the defeat of Lee Sedol by AlphaGo happened in 2016 and the use of AlphaFold in predicting protein structure in 2021, which demonstrated the unlimited potential of AI and kicked off booms in AI applications [36, 37]. Interestingly, the majority of the top 10 publications in the ranking of total citation count were published before 2018, while the majority of the top 10 publications in the ranking of annual citation count were published in the last five years, also indicating the growth in academic influence of research on AI in eyelid disease. In addition to the development of the AI technology, the reliability and advantages of AI applications demonstrated by these highly cited research was another reason for the rapid development of this field. The AI models applied to eyelid disease were proved to have good sensitivity and specificity, and the automated detection results produced by them were highly consistent with the manual detection results, which attracted more and more researchers to conduct relevant studies. Furthermore, in contrast to manual reviewers, the AI models could quantitatively assess target features by automatically reviewing image data, process large amounts of data quickly, avoid reviewer error and provide fully reproducible results. With these advantages, the application of AI on eyelid diseases was important for improving diagnostic efficiency and accuracy, developing personalized treatment plans and facilitating the development of telemedicine, which deserved the attention of researchers.

Researchers around the world have been involved in the research of AI applied to eyelid diseases. China was the most productive country in this field, followed by the USA. However, there was a huge gap between the numbers of publications of these two countries, which may be caused by the difference in the population and the number of eyelid diseases patients. When come to the co-authorship, USA had the most collaboration with other countries since it was the country with the most advanced AI technologies and research equipment. Wenzhou Medical University and Zhejiang University were the most productive and the most active in collaboration Chinese institutions. However, Wenzhou Medical University focused more on the meibomian gland dysfunction and using deep learning and transfer learning to segment meibomian gland and calculating the meibomian gland density for diagnosis [26], while Zhejiang University focused more on the blepharoptosis and using deep learning to automatically measure eyelid morphology before and after surgery [38].

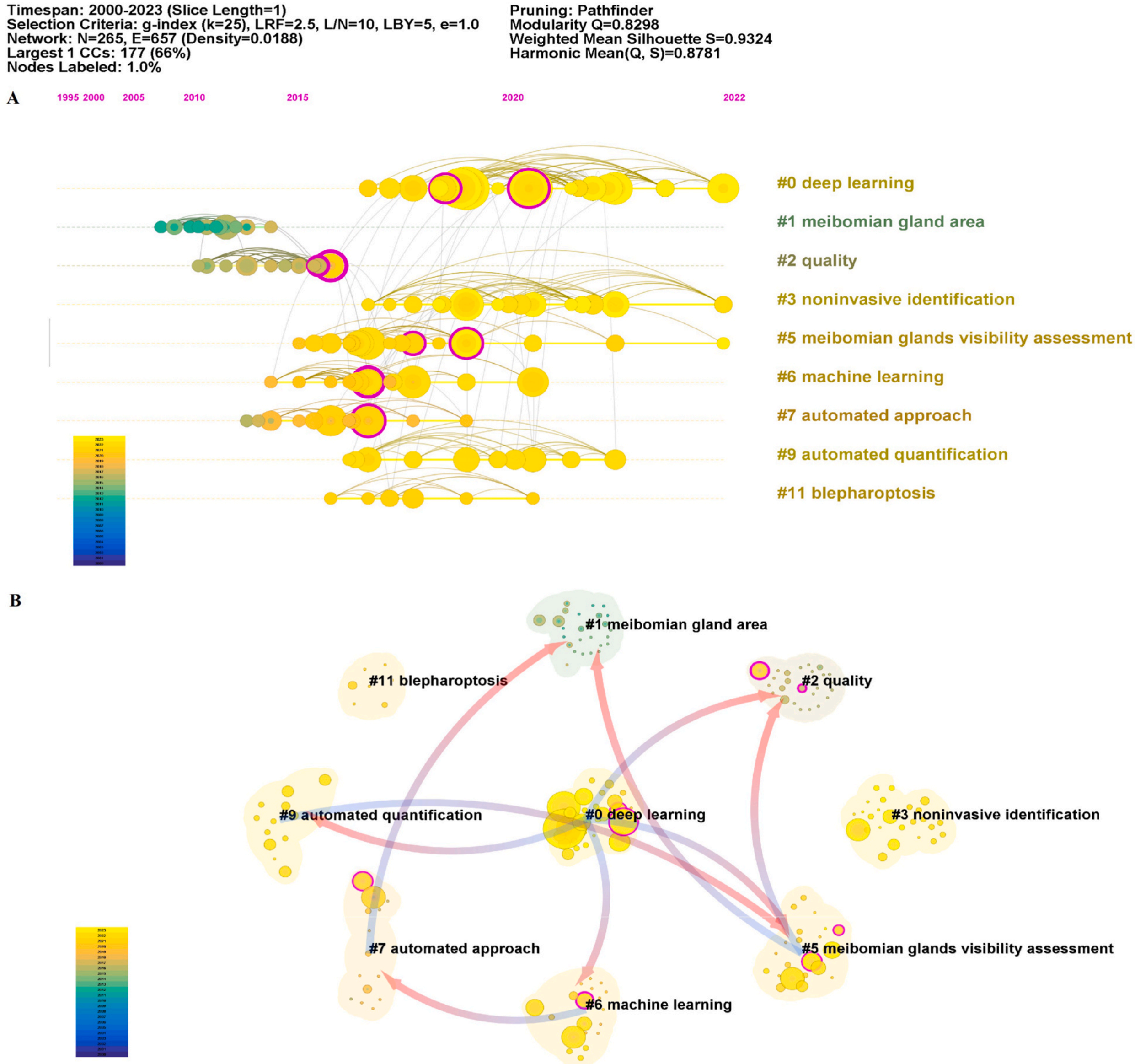


**Fig. 6. The timeline view and circular view of co-cited references network.** (A) The timeline map of co-cited references with major clusters; (B) The cluster dependencies of co-cited references.

The most popular research domains included Ophthalmology, Engineering Biomedical and Computer Science Artificial Intelligence, which reflected the interdisciplinary characteristics of research on AI in eyelid diseases. Although Ocular Surface was the most prolific journals, Translational Vision Science Technology and Biomedical Engineering Online published some high-impact publications, which were all about approaches to automatically assess the meibomian gland morphology [22,25,30]. Moreover, it is worth noting that because of less publication count, some influential journals with high average citation per publication might be overlooked, such as JAMA Ophthalmology, NPJ Digital Medicine and EClinicalMedicine [27,29,39]. It revealed that the total citation count did not fully reflect the quality of journals. It was hoped that more research papers in this field would be published in high quality journals in the future.

The research hotspots can be reflected by the frequently occurring keywords, and the mainstream topics can be made up of the co-occurred keywords. As shown in the co-occurrence network of keywords, blepharoptosis, meibomian gland dysfunction and blepharospasm were the most popular targeted diseases of the research on AI in eyelid diseases. It is easy to detect the mainstream topics of research on AI in these 3 diseases by respectively linking up the keywords in the same color, such as “automated measurement” of “margin reflex distance” based on “deep learning” using external ocular “images” of “blepharoptosis” patients, “meibomian gland segmentation” and “meibomian gland structure” evaluation based on “scribble-supervised” deep learning framework using “infrared meibography" of "meibomian gland dysfunction" patients and exploration of brain function abnormalities based on "support vector machine" using "resting-state functional magnetic resonance imaging" of "blepharospasm" patients. The evolution of the keyword demonstrated by the world cloud maps of different stages was consistent with the development of AI, which included statistical model period, neural network period and deep learning period [40]. Between 2000 and 2016, researchers were more concerned about measurement of clinical features (such as "meibomian gland", "eyelid" and "margin reflex distance") based on "image processing" algorithms for low-level computer vision task (such as super-resolution and denoise), and the representative publication was by Arita et al. in 2014 [20]. Between 2017 and 2020, researchers were more concerned about measuring clinical features based on "deep learning" for high-level computer vision task (such as detection and segmentation), and the representative publication was by Wang et al. in 2019 [22]. Between 2021 and 2023, researchers were more concerned about the application of AI to different clinical scenarios (such as "diagnosis" and "treatment") of eyelid diseases, and the two representative publications were by Huang et al. in 2021 and by Sun et al. in 2022 [11,41].

In the co-citation analysis and clustering analysis of the references, the cited references made up the clusters to provide the knowledge base, and the citing publications were used to generate the cluster labels to reveal the research frontiers. They formed the intellectual structure of AI applied to eyelid diseases together. It is interesting that the article by Wang et al. in 2019 in the cluster "0# deep learning" was both the cited references with the most citations and the citing publications included in the bibliometric analysis of this field, which demonstrated that this article was a landmark with groundbreaking contributions and might have a sustained impact on future research. With high betweenness centrality and degree centrality, the review by Baudouin et al. in 2016 in the cluster "2# quality" and the article by Esteva et al. in 2017 in the "6# machine learning" revealed the link between these two research frontiers, which corresponded to the two main themes of AI applied to eyelid diseases. Although cluster "0# deep learning" was the largest among these 9 major clusters, it appeared the latest. Moreover, as the CiteSpace only displayed the largest network with strong connections and some clusters were not connected to this network, the cluster label numbers shown in the figure were not consecutive. This information indicated that this field was nascent and there were still large gaps in it. The cluster "1# meibomian gland area" was the first to appear, followed by the cluster "2# quality", but these two research hotspots cooled rapidly over the decade. According to the cluster dependencies, they fused and generated a new research hotspot shown by the cluster "#5 meibomian glands visibility assessment", which continued to be a hot topic to this day and developed new research themes, such as cluster "0# deep learning" and cluster "9# automated quantification". This reflected that the integration and branching between the knowledge bases of different disciplines contributed to the development of the field.

There are some limitations in this study that should be noticed. Firstly, the publications of AI applied to eyelid diseases were all retrieved from WoS Core Collection to ensure that the full record of publications acquired has a harmonized format. Therefore, these publications included only in other databases (such as PubMed, Google Scholar and Scopus) were omitted. Secondly, the data analysis of this study was macroscopic. We focused only on publications at the top of rankings and meaningful frequent keywords, with neglect of the specific content and novelty of each article and these frequent keywords that appear very frequently but are not informative enough to analyze in depth (such as "method", "patients" and "algorithm"). Thirdly, there may be new publications every month due to rapidly evolving AI technologies, and the results of this study only reflected the current state of the art in this field.

## 5. Conclusion

This study revealed an overview of the global research of AI in eyelid diseases and was the first bibliometric analysis in this field, in which the annual trend of publications and citations, influential publications, productive countries/territories and institutions, co-authorship network, popular research domains and targeted sources and co-occurrence and evolution of keywords and co-citation and clustering of references were identified by analyzing 98 publications. Although the research of AI in eyelid diseases has entered a phase of rapid development in the last three years, there are still gaps between AI research and clinical applications. Our findings provide researchers with a better understanding of the development of the field and a reference for future research directions.

## Data availability

Data will be made available on request.

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## CRediT authorship contribution statement

**Xuan Zhang:** Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ziying Zhou:** Writing – review & editing, Validation. **Yilu Cai:** Writing – review & editing, Validation. **Andrzej Grzybowski:** Writing – review & editing, Validation. **Juan Ye:** Writing – review & editing, Validation, Funding acquisition. **Lixia Lou:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.


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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e34979.

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