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Research

Machine learning in ovarian cancer: a bibliometric and visual analysis from 2004 to 2024

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Abstract

Objective Ovarian cancer (OC) is a common malignant tumor in women, with poor prognosis and high mortality rates. Early diagnosis, screening, and prognostic prediction of OC have long been focal points and challenges in this field. In recent years, machine learning (ML) has gradually demonstrated its unique advantages in the early diagnosis, screening, and prognostic prediction of tumors, including OC.This study aims to analyze global development trends and research hotspots in the application of ML for OC, thereby providing a reference for future research directions.

Methods We searched the Web of Science Core Collection (WoSCC) for all publications related to OC and ML from 2004 to 2024, conducting a quantitative analysis using VOSviewer, R software, and CiteSpace.

Results A total of 777 articles were retrieved.The number of publications related to ML and OC has grown continuously over the past 20 years.China led with 254 articles.The most prominent journals include Gynecologic Oncology, Nature, Clinical Cancer Research, Cancer Research, and Journal of Clinical Oncology.Research hotspots are: (a) ML-driven OC biomarker discovery and personalized treatment; (b) ML in tumor microenvironment analysis and resistance prediction; (c) ML in imaging-based diagnosis and risk stratification; (d) ML in multicenter OC studies.

Conclusion ML in OC is currently in a developmental phase and shows promising potential for the future. This study provides researchers and clinicians with a more systematic understanding of research priorities and forthcoming developments in this area.

Keywords Machine learning · Deep learning · Ovarian cancer · Bibliometrics · Artificial intelligence

1 Introduction

OC is one of the most prevalent malignant tumors in women globally, characterized by poor prognosis and high mortality rates [1]. The mortality rate of OC is significantly correlated with the stage at diagnosis; for instance, the 5-year survival rate for women diagnosed at Stage I is 90% [2]. In cases of locally metastatic OC, this rate drops to approximately 80%, while those with distant metastasis face a further decline to around 25%. Regrettably, over 70% of OC cases are diagnosed at

Xian Zeng and Zude Li have contributed equally to this work and share first authorship

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Stage III or IV, when the disease is already advanced [3].Therefore, the search for screening initiatives capable of identifying early-stage changes in OC is crucial for reducing mortality rates among patients.

Moreover, the primary treatment for OC consists of cytoreductive surgery followed by adjuvant chemotherapy, with the first-line therapy typically involving a combination of platinum-based drugs and paclitaxel. The initial response rate to platinum-based chemotherapy ranges from 60 to 80%; however, some patients may develop drug resistance [4], and approximately 70% of those with platinum-resistant disease are likely to relapse within two years [5]. Before completing chemotherapy, the response of OC patients to platinum-based treatment remains uncertain, making the prediction of their response crucial. In summary, enhancing the survival rates of OC patients may require extensive research into various aspects, including early diagnosis, risk screening, and therapeutic decision-making [6, 7]. Throughout this research process, a significant amount of biomedical data is generated. Efficiently integrating and analyzing this data to provide clinical assistance presents a contemporary challenge, and ML is a vital tool in addressing this issue.

ML is a branch of artificial intelligence. In simple terms, ML algorithms analyze large volumes of data to mimic the human brain's processes of thinking, reasoning, and decision-making, ultimately addressing real-world issues [8, 9]. With the advancement of medical big data and computer technology, ML has been extensively utilized in contemporary cancer research [10–13]. ML methods have demonstrated significant potential in improving the accuracy of predictions related to cancer susceptibility, recurrence, and survival, with evidence indicating that their application has enhanced the accuracy of cancer forecasting by 15% to 20% in recent years [14]. With the advancement of ML in other oncological domains, an increasing number of researchers are utilizing ML for early screening, diagnosis, and treatment decision-making in OC. For instance, a recently published review highlighted the use of ML methods such as logistic regression, extreme gradient boosting, and support vector machines to predict the response of OC patients to platinum-based chemotherapy [4]. Another review highlighted the strong performance of ML algorithms in diagnosing OC through medical imaging; however, further external validation is needed to assess their accuracy [15]. Due to the limited number of publications, current reviews may not fully explore the latest research trends and hotspots in the application of ML in OC. Additionally, there is a lack of quantitative analysis across the existing literature in this field. Therefore, summarizing and quantitatively analyzing the global development trends and research hotspots of ML in OC is crucial for guiding future research.

Bibliometrics is an academic discipline that combines quantitative analysis (such as publication counts and citation frequencies) with qualitative analysis (such as thematic summarization) to analyze scholarly literature and its metadata (including authors, keywords, and citation relationships) [16]. Its primary objective is to elucidate the knowledge structure, developmental patterns, and underlying connections within a research domain [17]. Unlike traditional statistical methods that focus on relationships and causal inferences between variables, bibliometrics leverages techniques such as information visualization, knowledge mapping, co-word analysis, and co-citation analysis to intuitively depict the developmental trajectory, current status, hotspots, and trends of a research field, thereby providing a macroscopic overview of the research landscape. Bibliometrics has been widely applied for identifying research hotspots and predicting developmental trends across various disciplines [18–20].

Therefore, this study collects literature related to ML in the field of OC from the WoSCC database and employs bibliometric methods to quantitatively analyze the research process and current status over the past 20 years, while also predicting potential future research trends. This research will assist researchers and clinicians in this field in gaining a more systematic understanding of research focuses and upcoming trends.

2 Materials and methods

2.1 Data collection

The data for this study were obtained from the WoSCC database (Guangxi Medical University Purchase Edition) on December 31st, 2024. The search strategy is detailed in Table 1. All retrieved articles were saved in plain text format and exported as full records, including cited references.

2.2 Data analysis

The methodology employed in this study was based on previous research conducted by Li et al. [21, 22]. To analyze annual publication trends, Origin 2018 was used. Additionally, the analysis utilized R software (version 3.6.3) with

the bibliometrix package (version 4.0, http://www.bibliometrix.org) [23, 24], VOSviewer (version 1.6.17) [25], and CiteSpace (version 6.1.4) [26]. To ensure the accuracy and reliability of the data, two independent authors conducted data extraction and analysis management separately.

The bibliometrix package was utilized for visualizing and mapping scientific knowledge. VOSviewer was employed to construct visual representations of country and institutional co-authorship networks, source co-citation analysis, and keyword co-occurrence. For the co-authorship network, a minimum threshold was set to include countries or institutions with at least 5 publications. In the co-citation analysis, sources with a minimum of 50 citations were included. For keyword co-occurrence analysis, keywords with at least 5 occurrences were considered, while terms such as "ovarian cancer (OC)," "machine learning (ML)," "Artificial intelligence (AI)" and their synonyms were excluded [21]. Journal impact factors (IFs) were obtained from the 2023 edition of the Journal Citation Reports (JCR).

3 Results

3.1 Overview of selected studies on ML in OC

After removing duplicates, 777 distinct records were retrieved from the WoSCC database. From 2004 to 2024, the volume of publications related to ML and OC has consistently increased. Notably, there was a significant rise in publications following 2020, as illustrated in Fig. 1A. This increasing trend indicates that there is a growing academic and clinical interest in the application of ML to OC research.

An evaluation of the geographical distribution of corresponding authors revealed that China (n = 254) was the leading contributor, followed by the USA (n = 189), the United Kingdom (n = 45), Italy (n = 37), and India (n = 33). Furthermore, 62.2% of the publications from the United Kingdom involved multi-country collaborations (MCPs), as illustrated in Fig. 1B and detailed in Table 2. While China leads in publication volume, the United Kingdom demonstrates a more expansive and diverse international collaboration network, as shown in Fig. 2A. Additionally, the collaboration network identifies Fudan University (n = 18) and the Chinese Academy of Sciences (n = 14) as key hubs of collaborative activity (see Fig. 2B and Table 3). These findings indicate that Chinese scholars have a strong interest in applying ML to the treatment of OC.

3.2 Journal analysis and visualization

To investigate the journals that have made the most substantial contributions in terms of publication and citation within the domains of ML and OC, we utilized the Bibliometrix package in R software. Graphical representations were created using the ggplot2 package. Additionally, a co-citation analysis of the journals was conducted using VOSviewer. Our analysis identified a total of 777 documents distributed across 357 academic journals (see **Annex 1** for comprehensive details). As shown in Table 4 and illustrated in Fig. 3A, *Gynecologic Oncology* (n = 44, IF = 4.5) emerged as the leading publisher, followed by *Cancers* (n = 35, IF = 4.5), *Scientific Reports* (n = 31, IF = 3.8), *Frontiers in Oncology* (n = 23, IF = 3.5), and *International Journal of Molecular Sciences* (n = 10, IF = 4.9). Table 5 and Fig. 3B highlight the most frequently cited journals (see **Annex 2** for comprehensive details), with *Gynecologic Oncology* (n = 885, IF = 4.5), *Nature* (n = 658, IF = 50.5), *Clinical Cancer Research* (n = 612, IF = 10), *Cancer Research* (n = 551, IF = 12.5), and *Journal of Clinical Oncology* (n = 529, IF = 42.4) leading the list. Importantly, the co-citation map depicted in Fig. 4 illustrates that *Gynecologic Oncology*, *Nature*, and *Clinical Cancer Research* serve as pivotal collaboration hubs. These

Table 1 The research retrieval fomular of the field of ML in OC

Step	Search expression	Results
#1	TS = ("Ovarian cancer*" OR "Ovarian Neoplasm*" OR "Ovary Neoplasm*" OR "Ovary Cancer*" OR "Cancer of the Ovary" OR "Cancer of Ovary")	99,566
#2	TS = ("machine learning" OR "Learning Machine" OR "Artificial intelligence" OR AI OR "Transfer Learning" OR "Learning Transfer" OR "Deep learning" OR "Neural networks" OR "Unsupervised learning" OR "Supervised learning" OR "Reinforcement learning")	779,200
#3	(((#1 AND #2) AND DOP = (2004–01-01/2024–12-31)) AND DT = (Article OR Review)) AND LA = (English)	777

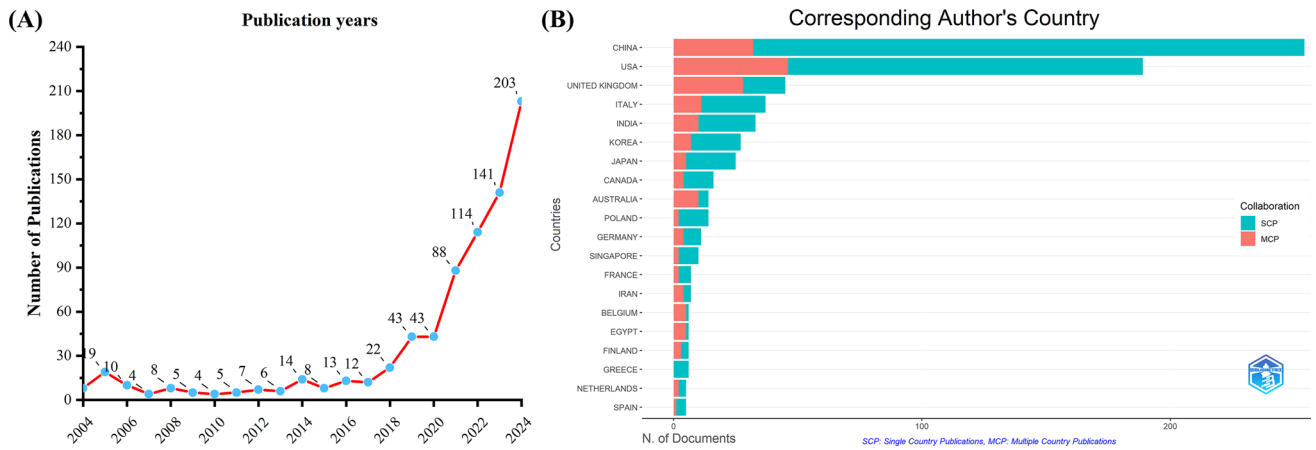

Fig. 1 Trends in annual publications in the field of ML in OC, 2004–2024. **A** Trends in publishing outputs, by year. **B** Distribution of corresponding authors countries and cooperation

Table 2 Most relevant countries by corresponding authors of ML in OC

Country	Articles	SCP	MCP	Freq	MCP_Ratio
China	254	222	32	0.327	0.126
USA	189	143	46	0.243	0.243
United Kingdom	45	17	28	0.058	0.622
Italy	37	26	11	0.048	0.297
India	33	23	10	0.042	0.303
Korea	27	20	7	0.035	0.259
Japan	25	20	5	0.032	0.2
Canada	16	12	4	0.021	0.25
Australia	14	4	10	0.018	0.714
Poland	14	12	2	0.018	0.143
Germany	11	7	4	0.014	0.364
Singapore	10	8	2	0.013	0.2
France	7	5	2	0.009	0.286
Iran	7	3	4	0.009	0.571
Belgium	6	1	5	0.008	0.833
Egypt	6	1	5	0.008	0.833
Finland	6	3	3	0.008	0.5
Greece	6	6	0	0.008	0
Netherlands	5	3	2	0.006	0.4
Spain	5	4	1	0.006	0.2

Note: MCP: Multiple country publication; SCP: Single country publication

results collectively emphasize the significant influence of *Gynecologic Oncology* and *Bioinformatics* within the context of ML in OC research.

3.3 Citation analysis

We utilized the Bibliometrix package in R software to identify the top 20 most-cited references in the field of ML in OC (Table 6). The three most cited papers were: "A Review of Feature Selection Techniques in Bioinformatics," "Calibration: The Achilles Heel of Predictive Analytics," and "Genomic and molecular landscape of DNA damage repair deficiency across the cancer genome atlas".

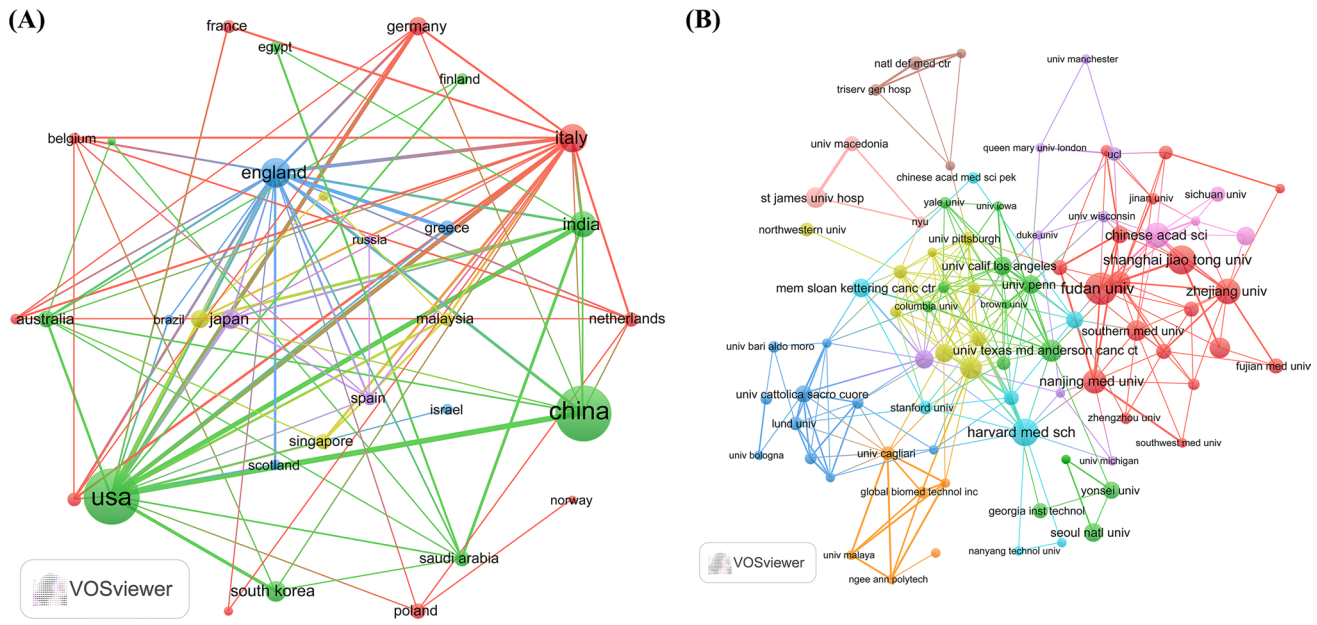

Fig. 2 Map of ML in OC Countries/Regions and Institutions, 2004–2024. **A** Map of cooperation between different countries. **B** Map of cooperation between different institutions

Table 3 Top 10 most relevant affiliations of ML in OC

Rank	Affliation	Articles (n)
1	Fudan Univ	18
2	Shanghai Jiao Tong Univ	16
3	Harvard Med Sch	15
3	Chinese Acad Sci	14
3	Zhejiang Univ	14
4	Nanjing Med Univ	13
4	Massachusetts Gen Hosp	12
5	Sun Yat Sen Univ	12
5	Univ Texas Md Anderson Canc Ctr	12
5	Southern Med Univ	11

Table 4 Top 10 journals with the most published

Sources	Documents	IF(2023)	Cites
Gynecologic Oncology	44	4.5	885
Cancers	35	4.5	407
Scientific Reports	31	3.8	498
Frontiers In Oncology	23	3.5	369
International Journal Of Molecular Sciences	10	4.9	226
Bioinformatics	9	4.4	485
Frontiers In Immunology	9	5.7	168
Journal of Ovarian Research	9	3.8	167
Nature Communications	9	14.7	434
PLoS One	9	2.9	429

To delve deeper into the exploration of the forefront and focal areas of ML in OC, we utilized CiteSpace to identify the top 15 most significant citation bursts related to ML in OC (refer to Fig. 5). The titles of these citations, along with their respective DOIs, are listed in **Annex 3**. Remarkably, the three citations exhibiting the most pronounced

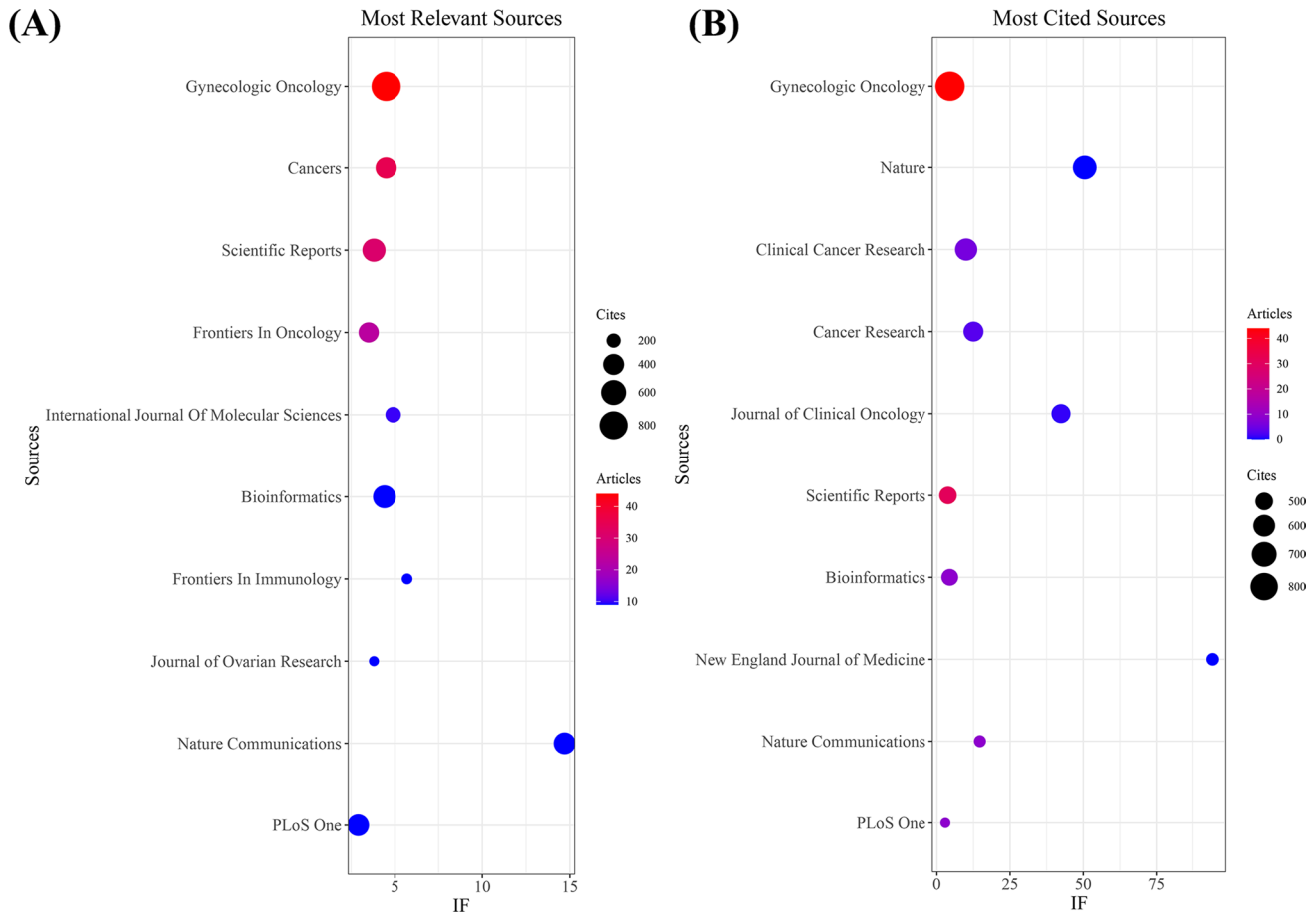

Fig. 3 Journal with the largest number of articles published and the journal with the largest number of citations. **A** Journal with the largest number of articles published. **B** Journals with the largest number of citations

Table 5 Top 10 journals with the most cited

Sources	Cites	IF(2023)	Documents
Gynecologic Oncology	885	4.5	44
Nature	658	50.5	0
Clinical Cancer Research	612	10	6
Cancer Research	551	12.5	3
Journal of Clinical Oncology	529	42.4	1
Scientific Reports	498	3.8	31
Bioinformatics	485	4.4	9
New England Journal of Medicine	437	94.3	0
Nature Communications	434	14.7	9
PLoS One	429	2.9	9

citation bursts were: (a) "Use of Proteomic Patterns in Serum to Identify OC (strength: 14.25)"; (b) "OC Statistics, 2018 (strength: 7.89)"; and (c) "Integrated genomic analyses of ovarian carcinoma (strength: 6.42)". Furthermore, the titles of the three most cutting-edge citation bursts were: (a) "Clinical-Grade Computational Pathology Using Weakly Supervised Deep Learning on Whole Slide Images"; (b) "MRI-based machine learning for differentiating borderline from malignant epithelial ovarian tumors: A multicenter study"; and (c) "Radiomics of high-grade serous ovarian cancer: association between quantitative CT features, residual tumour and disease progression within 12 months".

In general, through the analysis of cited literature and citation bursts, we identified three key research focuses in the field of ML and OC: (a) the discovery of OC biomarkers driven by ML and the development of personalized

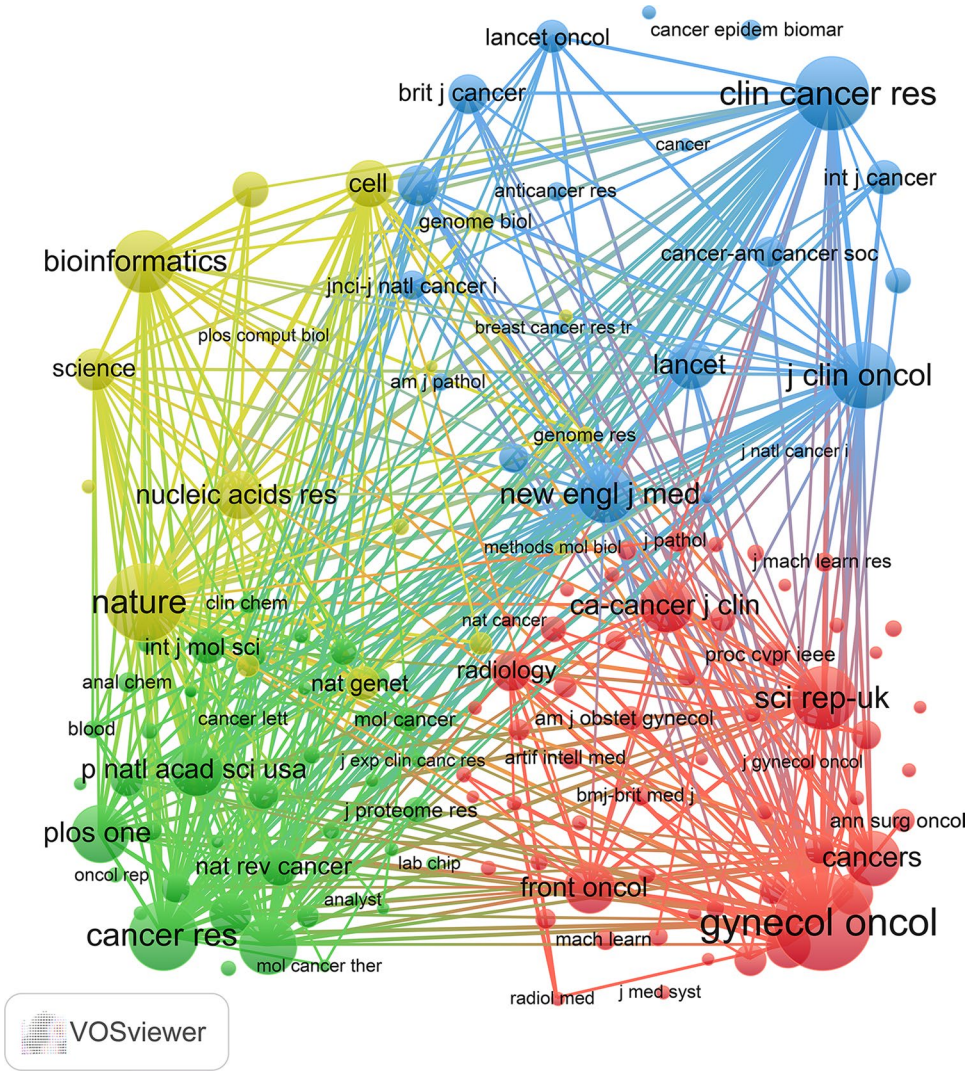

Fig. 4 ML in OC co-citation journals

treatment strategies; (b) the application of ML in analyzing the OC tumor microenvironment and predicting treatment resistance; and (c) the application of ML in imaging-based OC diagnosis and risk stratification.

3.4 Keyword clusters and evolution of themes

Keyword clusters are essential for quickly grasping the primary research themes and trends within a specific area. In our study, we utilized VOSviewer to identify 3249 keywords. Table 7 presents the top 20 keywords that appear more than 22 times, highlighting the main hotspots in the research. The most frequently occurring keyword was "classification" (n = 94), followed by " breast cancer " (n = 91), " diagnosis" (n = 81), "survival analysis" (n = 81), "expression" (n = 74), and " biomarkers " (n = 72).

Through cluster analysis, we observe six distinct colored clusters in Fig. 6. (a) The use of ML in exploring molecular mechanisms and precision medicine for OC treatment and prognosis (red dots) features 35 keywords, including expression, prognosis, immunotherapy, genes, and bioinformatics. (b) Prediction of genetic heterogeneity and treatment resistance in OC using ML (green dots) comprises 33 keywords, such as survival analysis, neoadjuvant chemotherapy, recurrence, mortality, and outcomes. (c) ML in personalized medicine and precision therapy for OC (blue dots) comprises 29 keywords, such as chemotherapy, resistance, validation, bevacizumab, and association. (d) ML in imaging diagnosis and preoperative evaluation in the field of OC (yellow dots) comprises 23 keywords, such as diagnosis, risk, models, radiomics,

Table 6 The top 20 cited references related to the ML in OC

Paper	DOI	Total Citations	TC per Year
SAEYS Y, 2007, BIOINFORMATICS	10.1093/bioinformatics/btm344	3380	177.89
VAN CALSTER B, 2019, BMC MED	10.1186/s12916-019–1466-7	834	119.14
KNIJNENBURG TA, 2018, CELL REP	10.1016/j.celrep.2018.03.076	719	89.88
KOZAK KR, 2005, PROTEOMICS	10.1002/pmic.200500093	251	11.95
MAJUMDER B, 2015, NAT COMMUN	10.1038/ncomms7169	223	20.27
DENG LJ, 2022, MOL CANCER	10.1186/s12943-022–01510-2	203	50.75
GULHAN DC, 2019, NAT GENET	10.1038/s41588-019–0390-2	197	28.14
BIRGISDOTTIR V, 2006, BREAST CANCER RES	10.1186/bcr1522	186	9.3
WARD DG, 2006, BRIT J CANCER	10.1038/sj.bjc.6603188	181	9.05
LIANG MX, 2015, IEEE ACM T COMPUT BI	10.1109/TCBB.2014.2377729	180	16.36
CHATTERJEE M, 2006, CANCER RES	10.1158/0008–5472.CAN-04–2962	179	8.95
GRUS FH, 2005, INVEST OPHTH VIS SCI	10.1167/iovs.04–0448	172	8.19
KRISHNAN AV, 2010, ENDOCRINOLOGY	10.1210/en.2009–0855	154	9.63
KATOH M, 2020, INT J MOL MED	10.3892/ijmm.2019.4418	152	25.33
DLAMINI Z, 2020, COMPUT STRUCT BIOTEC	10.1016/j.csbj.2020.08.019	138	23
LU HN, 2019, NAT COMMUN	10.1038/s41467-019–08718-9	129	18.43
KAWAKAMI E, 2019, CLIN CANCER RES	10.1158/1078–0432.CCR-18–3378	123	17.57
DESBOIS M, 2020, NAT COMMUN	10.1038/s41467-020–19408-2	122	20.33
WEI SH, 2006, CLIN CANCER RES	10.1158/1078–0432.CCR-05–1551	119	5.95
HARTMANN LC, 2005, CLIN CANCER RES	10.1158/1078–0432.CCR-04–1673	115	5.48

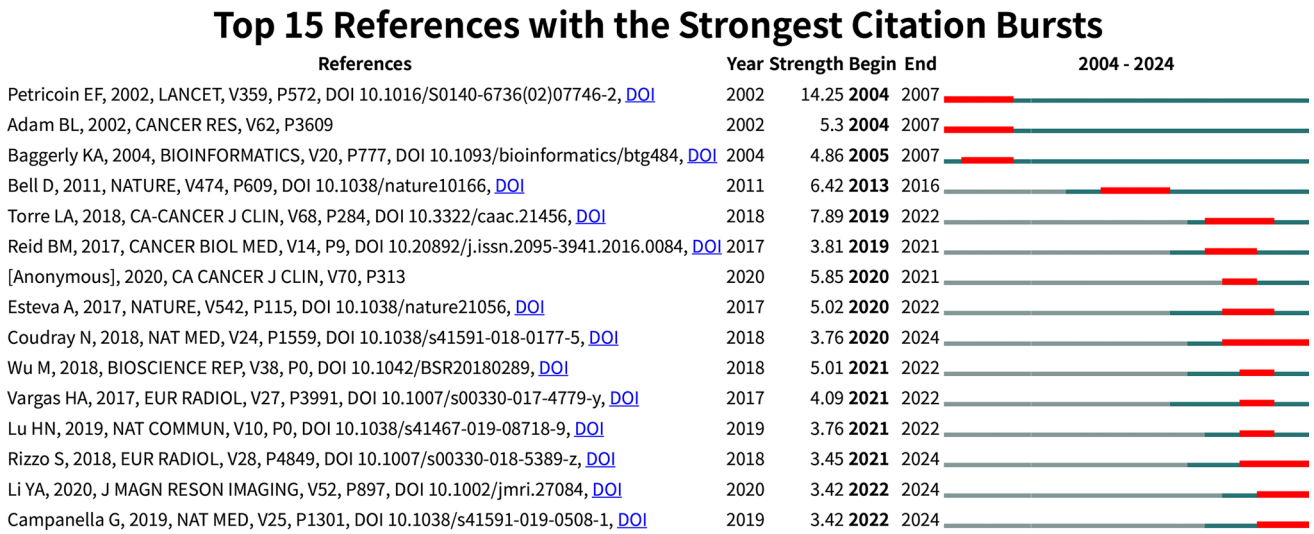

Fig. 5 Top 15 references with the strongest citation bursts on ML in OC

and ultrasonography. (e) ML in biomarker identification and multi-omics research in OC (purple dots) comprises 18 keywords, such as biomarkers, identification, mass spectrometry, CA-125, and protein. (f) Applications of ML and artificial intelligence in classification and prediction in OC research (cyan dots) comprises 18 keywords, such as classification, prediction, discovery, algorithm, and patterns. All keywords in the clusters are listed in **Annex 4**.

Additionally, to project upcoming trends within this domain, we employed the bibliometrix toolkit within the R programming environment to create a dynamic thematic progression chart (Fig. 7). From 2005 to 2019, the application of ML in cancer research evolved from basic proteomic pattern recognition to the exploration of disease mechanisms and

Table 7 The top 20 keywords related to ML in OC

Rank	Keywords	Count
1	Classification	94
2	Breast cancer	91
3	Diagnosis	81
4	Survival analysis	81
5	Expression	74
6	Biomarkers	72
7	Prediction	61
8	Prognosis	57
9	Chemotherapy	54
10	Risk	51
11	Models	47
12	Identification	41
13	Prostate cancer	40
14	Radiomics	39
15	Cells	37
16	Women	33
17	Mass spectrometry	32
18	Ca-125	30
19	Protein	29
20	Proteomics	28

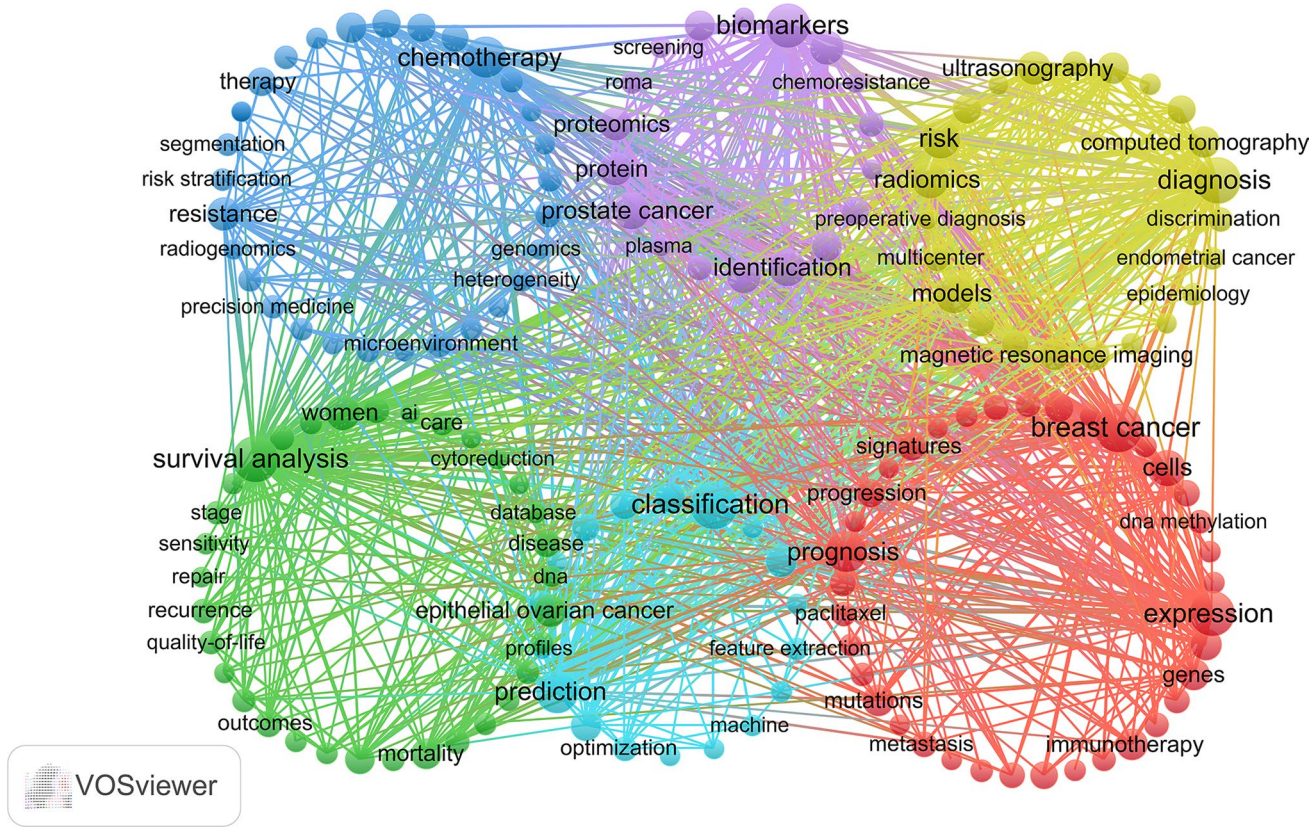

Fig. 6 Keywords co-occurrence map of publications on ML in OC research

biomarkers. In the early phase (2005–2006), researchers concentrated on identifying cancer-associated proteins through proteomic analysis and initial ML models, thereby establishing a foundation for diagnosis. In 2007–2008, research shifted focus to artificial neural networks and biomarker discovery, employing neural network models for large-scale data analysis to enhance OC screening. From 2009 to 2017, the research expanded to identify serum markers and gene expression, with ML aiding in the detection of early cancer signs. In 2018–2019, the focus turned to pathological mechanisms, mass spectrometry, and network analysis, using these tools to uncover the mechanisms and biomarkers of OC. From 2018 to 2021, validation and algorithm optimization became central themes, emphasizing the enhancement of ML algorithms for clinical applications. The research also prioritized medical image analysis and gene expression data classification to improve early detection and diagnostic accuracy. From 2022 to 2024, studies explored how ML could predict the stage and prognosis of OC. Currently, artificial intelligence and multicenter research are key areas of investigation, reflecting a pursuit of complex algorithms and their robustness and applicability in large-scale clinical trials.

3.5 Comprehensive analysis of hotspots

In summary, our comprehensive analysis, which includes citation burst detection, keyword frequency analysis, keyword clustering, and thematic evolution, has revealed emerging research frontiers at the intersection of ML and OC. Our findings indicate that the research hotspots in this field primarily focus on four key directions: (a) the discovery of OC biomarkers driven by ML and the development of personalized treatment strategies, (b) the application of ML in analyzing the OC tumor microenvironment and predicting treatment resistance, (c) the application of ML in imaging-based OC diagnosis and risk stratification, and (d) the application of ML in multicenter studies within the OC field.

4 Discussion

4.1 General information

With the advancement of medical big data and computational technologies, ML has been extensively utilized in cancer research, and the OC field is no exception. To delve into the research emphases and trends of ML in OC, we conducted a bibliometric and visualization analysis of relevant studies from 2004 to 2024, encompassing a total of 777 papers published during this period. Our findings indicate a notable upsurge in the number of papers on ML in OC since 2020, reflecting a growing interest in applying ML within the academic and clinical research communities. However, the volume of publications in this domain remains comparatively lower than in other cancer areas [10, 27], suggesting that research

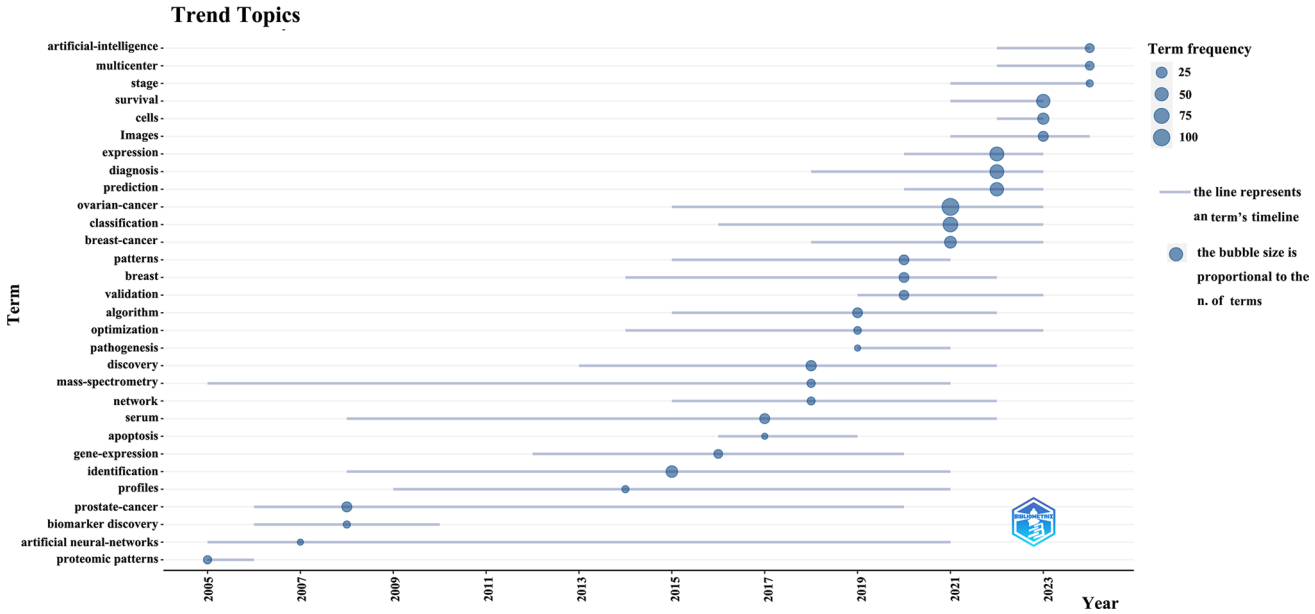

Fig. 7 Temporal Distribution and Proportion of Top 30 Terms on ML in OC Research

in this field is still in its nascent stages, with ample opportunities for growth. Geographically, China has emerged as the country with the highest number of published papers. This trend is similar to the ML research observed in several other cancer types [28, 29]. Notably, other leading countries in terms of publications include the United States, the United Kingdom, Italy, and India. While China leads in the volume of literature published, the United Kingdom demonstrates a broader and more diverse international collaboration network, with Fudan University and the Chinese Academy of Sciences serving as key hubs for collaboration. These results indicate that Chinese scholars have shown a strong interest in the application of ML to OC treatment.

The 777 papers are distributed across 357 journals, with *Cancers*, *Scientific Reports*, *Frontiers in Oncology*, *Gynecologic Oncology*, and *Bioinformatics* being the top five journals in terms of publication volume. Notably, the top five journals based on citation counts include *Gynecologic Oncology*, *Nature*, *Clinical Cancer Research*, *Bioinformatics*, and *Scientific Reports*, underscoring the significance of these journals in the research field.

4.2 Hotspots and development trends

Our comprehensive analysis, which includes citation burst detection, keyword frequency analysis, keyword clustering, and topic evolution, reveals emerging research frontiers at the intersection of ML and OC. The results indicate that research hotspots in this field are primarily concentrated in four key directions: (a) the discovery of OC biomarkers driven by ML and the development of personalized treatment strategies; (b) the application of ML in analyzing the OC tumor microenvironment and predicting treatment resistance; (c) the application of ML in imaging-based OC diagnosis and risk stratification; and (d) the application of ML in multicenter studies within the OC field.

4.2.1 The discovery of OC biomarkers driven by ML and the development of personalized treatment strategies

Cancer antigen 125 (CA125) is a commonly used biomarker for OC, with an elevated CA125 concentration (≥ 30 U/mL) serving as a predictive indicator for subsequent OC risk [30]. However, elevated CA125 levels in the range of 35–65 U/mL are challenging to distinguish between early-stage OC and benign gynecological conditions, such as endometriosis, since benign diseases can also elevate tumor marker levels [31]. Studies have shown that even the combined screening of vaginal ultrasound and CA125 has not been effective in reducing the mortality rate of OC, and there is a certain rate of false positives [32]. This indicates that the role of CA125 in OC screening is limited, highlighting the need for biomarkers with higher accuracy and specificity. ML algorithms can analyze vast amounts of biomedical data to identify novel biomarkers associated with OC and provide personalized treatment plans for patients. For instance, Gu et al. [33] found that OC exhibits a unique postprandial serum CA125 increase compared to benign ovarian diseases. Based on this finding, they constructed an SVM-based CA125 increment algorithm, reportedly achieving a sensitivity of 91.7% and a specificity of 99.2% in detecting early-stage OC. Similarly, Jerry Z et al. [34] screened 34 metabolites that showed significant differences in the urine of healthy adults and OC patients, establishing a classification model that achieved a maximum accuracy rate of 85.29%. Additionally, ML models play a crucial role in predicting the response of OC patients to chemotherapy drugs, such as platinum, aiding physicians in selecting more effective personalized treatment methods [15, 35, 36]. However, the "black box" issue in using ML to discover OC biomarkers limits practical application, as physicians and patients need to understand the basis of the model's predictions; thus, model interpretability is vital. To address this challenge, an increasing number of studies are applying Shapley analysis to quantify the importance of features in ML models, thereby enhancing their interpretability [37, 38].

4.2.2 The application of ML in analyzing the OC tumor microenvironment and predicting treatment resistance

ML in the analysis of the OC tumor microenvironment and prediction of treatment resistance primarily involves analyzing a vast array of data from the tumor microenvironment, including genomic, transcriptomic, proteomic, and clinical data [4, 39, 40], to identify patterns and biomarkers associated with tumor growth, invasion, and treatment response. These patterns are crucial for forecasting treatment efficacy and patient prognosis. For instance, Zhao et al. [41] screened macrophage-related markers from The Cancer Genome Atlas OC dataset using weighted gene co-expression network analysis. These markers were then submitted to 10 ML algorithms to construct a prognostic prediction model, which reportedly outperformed traditional grading and staging in predicting overall survival rates in OC. Wu et al. [42] screened

genes associated with the tumor microenvironment and prognosis from seven datasets, including The Cancer Genome Atlas. They submitted these genes to ML algorithms to develop a risk scoring model related to the tumor microenvironment. Patients with low scores exhibited BRCA1 mutations, immune activation, and a favorable immune response, while those with high scores were significantly associated with deficiencies in C-X-C motif chemokine ligands and the activation of oncogenic pathways. Current research indicates that ML models can effectively distinguish different subtypes of OC, assess the impact of the tumor microenvironment, and predict resistance to chemotherapy or immunotherapy [43, 44]. However, ML also faces limitations in analyzing the OC tumor microenvironment and predicting therapeutic resistance [45]. Firstly, the accuracy of the model is highly dependent on the quality and quantity of the training data; biased or incomplete training data can compromise predictive power. Secondly, the selected genes related to the OC microenvironment require further in vitro and in vivo experiments to confirm their functions. Additionally, the heterogeneity and dynamic changes of the tumor microenvironment complicate predictions. Despite these challenges, advancements in technology and the availability of higher-quality data make the application prospects of ML in this field promising.

4.2.3 The application of ML in imaging-based OC diagnosis and risk stratification

By leveraging medical imaging data, such as computed tomography (CT), ultrasound imaging, and magnetic resonance imaging (MRI) [46], ML models can identify and extract features that are valuable for the diagnosis and prognostic prediction of OC. These models have shown great potential in enhancing the accuracy [15, 47, 48], efficiency, and prognostic assessment [53–54]of diagnostic procedures.Research indicates that ML models have made significant progress in imaging-based diagnosis of OC, pathological classification, guidance for targeted biopsies, and prognosis prediction [15, 47, 50]. For instance, through radiomic features, ML models can distinguish between different types of OC, such as epithelial OC and borderline epithelial ovarian tumors [51], thereby aiding clinical decision-making. Furthermore, by analyzing preoperative and postoperative imaging features, ML is also utilized to predict recurrence and prognosis of OC, as well as to forecast progression-free survival and overall survival for patients [52–54]. In terms of risk stratification, ML models can more accurately predict treatment response and prognosis for OC patients by integrating clinical, pathological, and radiomic data [49, 50, 55]. For example, by analyzing the imaging and pathological characteristics of tumors, quantitative features associated with prognosis can be identified, leading to more personalized treatment plans for patients [52]. Current research indicates that ML models can effectively distinguish different subtypes of OC, assess the impact of the tumor microenvironment, and predict resistance to chemotherapy or immunotherapy [43, 44].Despite the significant potential of ML in the diagnosis and risk stratification of OC, most current studies are retrospective and have limited sample sizes. Future research needs to further test and verify the performance of these models in prospective, large-scale studies [56]. Additionally, enhancing the models' generalizability and interpretability will be a key focus for future research [57]. Overall, ML technology is playing an increasingly important role in the imaging diagnosis and risk stratification of OC and is expected to have a greater impact on future clinical practice.

4.2.4 The application of ML in multicenter studies within the OC field

The application of ML in multicenter studies on OC is progressively expanding. For example, Gao et al. [47] developed a deep convolutional neural network model using pelvic ultrasound images from seven hospitals in China. They not only validated the model's accuracy on an internal validation set but also tested its generalization ability using data from two additional hospitals as an external validation set. Leng et al. [58] utilized data from patients with epithelial OC across three centers to develop an integrated model through ML algorithms. This model incorporated radiomic features along with clinical features to predict the FIGO staging of OC patients, demonstrating exceptional predictive performance in EOC staging, outperforming both the clinical feature model and the radiomic model. Li et al., through the analysis of MRI images from 501 confirmed OC cases across eight clinical centers, utilized ML algorithms to establish a model that distinguishes between borderline epithelial ovarian tumors and malignant ovarian tumors, demonstrating robust performance superior to the subjective assessment of radiologists [59]. Despite these advancements, multicenter studies in this domain also have certain limitations. Firstly, most current research is retrospective, necessitating prospective data for more compelling evidence. Secondly, there is a lack of international collaboration in current studies; incorporating data from patients of diverse ethnicities globally could enhance the model's generalizability and performance. In summary,

multicenter collaboration is a significant trend for future applications of ML in the OC field, emphasizing the need for increased international cooperation and more prospective studies to improve model accuracy and generalizability.

4.3 Advantages and limitations

In this study, we conducted the first bibliometric analysis of the application of ML in the field of OC. Through the analysis of current and future trends in this field by this study, researchers and clinicians in this domain will be able to systematically understand the research priorities and future trends in this area. However, several limitations must be acknowledged. Firstly, the data were sourced exclusively from the WoSCC, which may lead to the omission of relevant literature from other databases and introduce potential biases. Additionally, the study was restricted to English-language publications, which may limit the comprehensiveness and representativeness of the findings. Thirdly, while bibliometric methods are effective in identifying research hotspots and trends, they have limitations in conducting in-depth analyses of specific study contents and quality. Therefore, future research should incorporate multiple databases (such as PubMed and Scopus) and include publications in various languages to provide a more comprehensive and unbiased overview of the research landscape.

5 Conclusion

This study employed bibliometric analysis to comprehensively examine the application of ML in OC from 2004 to 2024. The analysis revealed global developmental trends, research hotspots, and future directions in this domain, highlighting the potential of ML to enhance early diagnosis, treatment, and prognosis of OC. Based on the findings of this study, the following recommendations are proposed to guide future research on the application of ML in OC. Firstly, future research should prioritize the development of interpretable ML models to enhance transparency and provide insights into the decision-making process. This will help clinicians and patients better understand the basis for model predictions, thereby addressing the "black box" challenge often associated with complex algorithms. Secondly, future studies should expand international collaboration by including diverse patient populations and datasets from multiple regions. This approach will not only enhance the robustness and generalizability of ML models but also promote the development of globally applicable diagnostic and prognostic tools. Third, prospective and large-scale validation studies are essential. Future research should focus on validating ML models in real-world clinical settings through prospective, large-scale trials to ensure their accuracy and reliability in clinical practice. Finally, translating ML models into real-world clinical applications remains a key priority. Although numerous studies have demonstrated the potential of ML in OC research, its actual clinical application remains limited. Future research should focus on pilot studies and randomized controlled trials to assess the impact of ML on clinical outcomes and patient care, thereby bridging the gap between theoretical potential and practical implementation.

Author contributions XZ and ZL were responsible for data analysis and manuscript preparation. Data collection was performed by LD. JL revised the language of the manuscript. LL and WC designed the study and offered critical revisions of the manuscript. All authors have significantly contributed to the conception, execution, and intellectual content of this work, and have given their final approval for the version submitted for publication.

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Data availability Data is provided within the manuscript or supplementary information files.

Declarations

Competing interests The authors declare no competing interests.

References

1. Sung H, Ferlay J, Siegel RL, Laversanne M, Soerjomataram I, Jemal A, et al. Global Cancer Statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J Clin. 2021;71(3):209–49. https://doi.org/10.3322/caac.21660.
2. Vargas AN. Natural history of ovarian cancer Ecancermedicalscience. 2014;25(8):465. https://doi.org/10.3332/ecancer.2014.465.PMID:25371706;PMCID:PMC4176445.
3. Stewart C, Ralyea C, Lockwood S. Ovarian cancer: an integrated review. Semin Oncol Nurs. 2019;35(2):151–6. https://doi.org/10.1016/j.soncn.2019.02.001.
4. Wang Q, Chang Z, Liu X, Wang Y, Feng C, Ping Y, et al. Predictive value of machine learning for platinum chemotherapy responses in ovarian cancer: systematic review and meta-analysis. J Med Internet Res. 2024;22(26): e48527. https://doi.org/10.2196/48527.
5. Lheureux S, Braunstein M, Oza AM. Epithelial ovarian cancer: evolution of management in the era of precision medicine. CA Cancer J Clin. 2019;69(4):280–304. https://doi.org/10.3322/caac.21559.
6. Ahamad MM, Aktar S, Uddin MJ, Rahman T, Alyami SA, Al-Ashhab S, et al. Early-stage detection of ovarian cancer based on clinical data using machine learning approaches. J Pers Med. 2022;12(8):1211. https://doi.org/10.3390/jpm12081211.
7. Sah S, Bifarin OO, Moore SG, Gaul DA, Chung H, Kwon SY, et al. Serum lipidome profiling reveals a distinct signature of ovarian cancer in korean women. Cancer Epidemiol Biomarkers Prev. 2024;33(5):681–93. https://doi.org/10.1158/1055-9965.EPI-23-1293.
8. Ngiam KY, Khor IW. Big data and machine learning algorithms for health-care delivery. Lancet Oncol. 2019;20(5):e262–73. https://doi.org/10.1016/S1470-2045(19)30149-4 (**Erratum. In: Lancet Oncol. 2019;20(6):293. doi: 10.1016/S1470-2045(19)30294-3**).
9. Handelman GS, Kok HK, Chandra RV, Razavi AH, Lee MJ, Asadi H. eDoctor: machine learning and the future of medicine. J Intern Med. 2018;284(6):603–19. https://doi.org/10.1111/joim.12822.
10. Huang P, Feng Z, Shu X, Wu A, Wang Z, Hu T, et al. A bibliometric and visual analysis of publications on artificial intelligence in colorectal cancer (2002–2022). Front Oncol. 2023;7(13):1077539. https://doi.org/10.3389/fonc.2023.1077539.
11. Mitsala A, Tsalikidis C, Pitiakoudis M, Simopoulos C, Tsaroucha AK. Artificial intelligence in colorectal cancer screening, diagnosis and treatment. A new era. Curr Oncol. 2021;28(3):1581–607. https://doi.org/10.3390/curroncol28030149.
12. Uchikov P, Khalid U, Kraev K, Hristov B, Kraeva M, Tenchev T, et al. Artificial intelligence in the diagnosis of colorectal cancer: a literature review. Diagnostics (Basel). 2024;14(5):528. https://doi.org/10.3390/diagnostics14050528.
13. Bhinder B, Gilvary C, Madhukar NS, Elemento O. Artificial intelligence in cancer research and precision medicine. Cancer Discov. 2021;11(4):900–15. https://doi.org/10.1158/2159-8290.CD-21-0090.
14. Cruz JA, Wishart DS. Applications of machine learning in cancer prediction and prognosis. Cancer Inform. 2007;11(2):59–77.
15. Xu HL, Gong TT, Liu FH, Chen HY, Xiao Q, Hou Y, et al. Artificial intelligence performance in image-based ovarian cancer identification: a systematic review and meta-analysis. EClinicalMedicine. 2022;17(53): 101662. https://doi.org/10.1016/j.eclinm.2022.101662.
16. Ninkov A, Frank JR, Maggio LA. Bibliometrics: methods for studying academic publishing. Perspect Med Educ. 2022;11(3):173–6. https://doi.org/10.1007/s40037-021-00695-4.
17. bdelwahab SI, Taha MME, Farasani A, Abdullah SM, Moshi JM, Alshahrani AF, et al. Bibliometric analysis: A few suggestions (Part Two). Curr Probl Cardiol. 2025;50(3): 102982. https://doi.org/10.1016/j.cpcardiol.2025.102982.
18. Mao J, Li C, Wu F, Wang Y, Zhu J, Wen C. The relationship between kidney disease and mitochondria: a bibliometric study. Ren Fail. 2024;46(1):2302963. https://doi.org/10.1080/0886022X.2024.2302963.
19. Cai D, Xu F, Bai L, Liu Z. A landscape of globe research trends on minimally invasive glaucoma surgical techniques: a correspondence on bibliometrics analysis. Int J Surg. 2024;110(12):8195–7. https://doi.org/10.1097/JS9.0000000000001787.
20. Li Z, Liao X, Qin Y, et al. Exploring the impact of coffee consumption on liver health: a comprehensive bibliometric analysis. Heliyon. 2024;10(10): e31132. https://doi.org/10.1016/j.heliyon.2024.e31132.
21. Li Z, Liao X, Qin Y, Jiang C, Lian Y, Lin X, et al. Exploring the impact of coffee consumption on liver health: a comprehensive bibliometric analysis. Heliyon. 2024;10(10): e31132. https://doi.org/10.1016/j.heliyon.2024.e31132.
22. Dong Y, Liu L, Han J, et al. Worldwide research trends on artemisinin: a bibliometric analysis from 2000 to 2021. Front Med (Lausanne). 2022;9: 868087. https://doi.org/10.3389/fmed.2022.868087.
23. Aria M, Cuccurullo C. bibliometrix: An R-tool for comprehensive science mapping analysis. J Informet. 2017;11(4):959–75.
24. Li Z, Li A, Liu P, Zhang B, Yan Y. Mapping the evolution and impact of ketogenic diet research on diabetes management: a comprehensive bibliometric analysis from 2005 to 2024. Front Nutr. 2024;11:1485642. https://doi.org/10.3389/fnut.2024.1485642.
25. Van-Eck N, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics. 2010;84(2):523–38.
26. Chen C. CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature. J Am Soc Inform Sci Technol. 2006;57(3):359–77.
27. Zhong R, Gao T, Li J, Li Z, Tian X, Zhang C, et al. The global research of artificial intelligence in lung cancer: a 20-year bibliometric analysis. Front Oncol. 2024;2(14):1346010. https://doi.org/10.3389/fonc.2024.1346010.

28. Yin H, Zhang F, Yang X, Meng X, Miao Y, Noor Hussain MS, et al. Research trends of artificial intelligence in pancreatic cancer: a bibliometric analysis. Front Oncol. 2022;2(12): 973999. https://doi.org/10.3389/fonc.2022.973999.
29. Xiong M, Xu Y, Zhao Y, He S, Zhu Q, Wu Y, et al. Quantitative analysis of artificial intelligence on liver cancer: a bibliometric analysis. Front Oncol. 2023;16(13): 990306. https://doi.org/10.3389/fonc.2023.990306.
30. Jacobs IJ, Skates S, Davies AP, Woolas RP, Jeyerajah A, Weidemann P, et al. Risk of diagnosis of ovarian cancer after raised serum CA 125 concentration: a prospective cohort study. BMJ. 1996;313(7069):1355–8. https://doi.org/10.1136/bmj.313.7069.1355.
31. Akazawa M, Hashimoto K. Artificial intelligence in ovarian cancer diagnosis. Anticancer Res. 2020;40(8):4795–800. https://doi.org/10.21873/anticanres.
32. Buys SS, Partridge E, Black A, Johnson CC, Lamerato L, Isaacs C, et al. Effect of screening on ovarian cancer mortality: the Prostate, Lung, Colorectal and Ovarian (PLCO) Cancer Screening Randomized Controlled Trial. JAMA. 2011;305(22):2295–303. https://doi.org/10.1001/jama.2011.766.
33. Gu Z, He Y, Zhang Y, Chen M, Song K, Huang Y, et al. Postprandial increase in serum CA125 as a surrogate biomarker for early diagnosis of ovarian cancer. J Transl Med. 2018;16(1):114. https://doi.org/10.1186/s12967-018-1489-4.
34. Yao JZ, Tsigelny IF, Kesari S, Kouznetsova VL. Diagnostics of ovarian cancer via metabolite analysis and machine learning. Integr Biol (Camb). 2023;11(15):005. https://doi.org/10.1093/intbio/zyad005.
35. Shannon NB, Tan LLY, Tan QX, Tan JW, Hendrikson J, et al. A machine learning approach to identify predictive molecular markers for cisplatin chemosensitivity following surgical resection in ovarian cancer. Sci Rep. 2021;11(1):16829. https://doi.org/10.1038/s41598-021-96072-6.
36. Lan C, Li J, Huang X, Heindl A, Wang Y, Yan S, et al. Stromal cell ratio based on automated image analysis as a predictor for platinum-resistant recurrent ovarian cancer. BMC Cancer. 2019;19(1):159. https://doi.org/10.1186/s12885-019-5343-8.
37. Huang W, Suominen H, Liu T, Rice G, Salomon C, Barnard AS. Explainable discovery of disease biomarkers: the case of ovarian cancer to illustrate the best practice in machine learning and Shapley analysis. J Biomed Inform. 2023;141: 104365. https://doi.org/10.1016/j.jbi.2023.104365.
38. Wu M, Zhao Y, Dong X, Jin Y, Cheng S, Zhang N, et al. Artificial intelligence-based preoperative prediction system for diagnosis and prognosis in epithelial ovarian cancer: A multicenter study. Front Oncol. 2022;21(12): 975703. https://doi.org/10.3389/fonc.2022.975703.
39. Farinella F, Merone M, Bacco L, Capirchio A, Ciccozzi M, Caligiore D. Machine Learning analysis of high-grade serous ovarian cancer proteomic dataset reveals novel candidate biomarkers. Sci Rep. 2022;12(1):3041. https://doi.org/10.1038/s41598-022-06788-2.
40. Hamidi F, Gilani N, Arabi Belaghi R, Yaghoobi H, Babaei E, Sarbakhsh P, et al. Identifying potential circulating miRNA biomarkers for the diagnosis and prediction of ovarian cancer using machine-learning approach: application of Boruta. Front Digit Health. 2023;9(5):1187578. https://doi.org/10.3389/fdgth.2023.1187578.
41. Zhao B, Pei L. A macrophage related signature for predicting prognosis and drug sensitivity in ovarian cancer based on integrative machine learning. BMC Med Genomics. 2023;16(1):230. https://doi.org/10.1186/s12920-023-01671-z.
42. Wu Q, Tian R, He X, Liu J, Ou C, Li Y, et al. Machine learning-based integration develops an immune-related risk model for predicting prognosis of high-grade serous ovarian cancer and providing therapeutic strategies. Front Immunol. 2023;5(14):1164408. https://doi.org/10.3389/fimmu.2023.1164408.
43. Zhang C, Yang J, Chen S, Sun L, Li K, Lai G, et al. Artificial intelligence in ovarian cancer drug resistance advanced 3PM approach: subtype classification and prognostic modeling. EPMA J. 2024;15(3):525–44. https://doi.org/10.1007/s13167-024-00374-4.
44. Jiménez-Sánchez A, Cybulska P, Mager KL, Koplev S, Cast O, Couturier DL, et al. Unraveling tumor-immune heterogeneity in advanced ovarian cancer uncovers immunogenic effect of chemotherapy. Nat Genet. 2020;52(6):582–93. https://doi.org/10.1038/s41588-020-0630-5. (**Epub 2020 Jun 1**).
45. Walsh LA, Quail DF. Decoding the tumor microenvironment with spatial technologies. Nat Immunol. 2023;24(12):1982–93. https://doi.org/10.1038/s41590-023-01678-9.
46. Koch AH, Jeelof LS, Muntinga CLP, Gootzen TA, van de Kruis NMA, Nederend J, et al. Analysis of computer-aided diagnostics in the preoperative diagnosis of ovarian cancer: a systematic review. Insights Imaging. 2023;14(1):34. https://doi.org/10.1186/s13244-022-01345-x.
47. Gao Y, Zeng S, Xu X, Li H, Yao S, Song K, et al. Deep learning-enabled pelvic ultrasound images for accurate diagnosis of ovarian cancer in China: a retrospective, multicentre, diagnostic study. Lancet Digit Health. 2022;4(3):e179–87. https://doi.org/10.1016/S2589-7500(21)00278-8.
48. Jm SL, Subbulakshmi P. Innovative approach towards early prediction of ovarian cancer: machine learning-enabled XAI techniques. Heliyon. 2024;10:9.
49. Sidey-Gibbons CJ, Sun C, Schneider A, Lu SC, Lu K, Wright A, et al. Predicting 180-day mortality for women with ovarian cancer using machine learning and patient-reported outcome data. Sci Rep. 2022;12(1):21269. https://doi.org/10.1038/s41598-022-22614-1.
50. Boehm KM, Aherne EA, Ellenson L, Nikolovski I, Alghamdi M, Vázquez-García I, et al. Multimodal data integration using machine learning improves risk stratification of high-grade serous ovarian cancer. Nat Cancer. 2022;3(6):723–33. https://doi.org/10.1038/s43018-022-00388-9.
51. Chen J, Liu L, He Z, Su D, Liu C. CT-Based Radiomics and Machine Learning for Differentiating Benign, Borderline, and Early-Stage Malignant Ovarian Tumors. J Imaging Inform Med. 2024;37(1):180–95. https://doi.org/10.1007/s10278-023-00903-z.
52. Fu L, Wang W, Lin L, Gao F, Yang J, Lv Y, et al. Multitask prediction models for serous ovarian cancer by preoperative CT image assessments based on radiomics. Front Med (Lausanne). 2024;6(11):1334062. https://doi.org/10.3389/fmed.2024.1334062.
53. Abdoli N, Zhang K, Gilley P, Chen X, Sadri Y, Thai T, et al. Evaluating the Effectiveness of 2D and 3D CT Image Features for Predicting Tumor Response to Chemotherapy. Bioengineering (Basel). 2023;10(11):1334. https://doi.org/10.3390/bioengineering10111334.
54. Hsu WH, Ko AT, Weng CS, Chang CL, Jan YT, Lin JB, et al. Explainable machine learning model for predicting skeletal muscle loss during surgery and adjuvant chemotherapy in ovarian cancer. J Cachexia Sarcopenia Muscle. 2023;14(5):2044–53. https://doi.org/10.1002/jcsm.13282.
55. Zeng H, Chen L, Zhang M, Luo Y, Ma X. Integration of histopathological images and multi-dimensional omics analyses predicts molecular features and prognosis in high-grade serous ovarian cancer. Gynecol Oncol. 2021;163(1):171–80. https://doi.org/10.1016/j.ygyno.2021.07.015.

56. Seidelmann SB, Claggett B, Cheng S, Henglin M, Shah A, Steffen LM, et al. Dietary carbohydrate intake and mortality: a prospective cohort study and meta-analysis. Lancet Public Health. 2018;3(9):e419–28. https://doi.org/10.1016/S2468-2667(18)30135-X.
57. Akazawa M, Hashimoto K. Artificial intelligence in gynecologic cancers: current status and future challenges - A systematic review. Artif Intell Med. 2021;120: 102164. https://doi.org/10.1016/j.artmed.2021.102164.
58. Leng Y, Kan A, Wang X, Li X, Xiao X, Wang Y, et al. Contrast-enhanced CT radiomics for preoperative prediction of stage in epithelial ovarian cancer: a multicenter study. BMC Cancer. 2024;24(1):307. https://doi.org/10.1186/s12885-024-12037-8.
59. Li Y, Jian J, Pickhardt PJ, Ma F, Xia W, Li H, et al. MRI-based machine learning for differentiating borderline from malignant epithelial ovarian tumors: a multicenter study. J Magn Reson Imaging. 2020;52(3):897–904. https://doi.org/10.1002/jmri.27084.