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Research Article

Photonic Neuromorphic Computing Trends in the Global Research

Danish Rashid Shah[1], Muneer Ahmad[2] and Ashaq Hussain Dar[3]
[1]Allama Iqbal Library, University of Kashmir, Srinagar, Jammu & Kashmir, India
[2]The Iddi Basajjabalaba Memorial Library, Kampala International University, Uganda
[3]Library, University of Kashmir, Srinagar, Jammu and Kashmir, India

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Correspondence*
danish99shah@gmail.com

ORCID
Danish Rashid Shah
https://orcid.org/0009-0004-9028-4963
Muneer Ahmad
https://orcid.org/0000-0001-5666-8438
Ashaq Hussain Dar
https://orcid.org/0009-0001-1034-5024

Abstract

Neuromorphic computing in photonics aims at replicating the information processing capabilities of the brain using photonic devices and provides a platform for energy-efficient hardware in artificial intelligence. Expert reviews describe the technology well, but rarely provide a complete picture of the entire field. This study uses records from to map the field, covering all years and all document types. The tools Excel, HistCite, biblioshiny and VOSviewer were used to determine trends in publications, establish which countries were the dominant ones, identify the most productive and influential authors, determine the dominant themes of the literature and how these have evolved over time, and establish which studies and clusters of studies make up the body of knowledge that future research has been based upon. The results show an initial burst of activity in the domain of optical neural networks, a long quiet period, and then a rapid and sustained increase in recent years. China has the largest share of papers and one university produces the most productive authors. However, papers from North America and parts of Europe receive more citations on average and involve more international teamwork. A different set of authors, based mainly at Princeton and Queen's University, are the most influential. Keywords form clear groups around optical neural networks, laser-based spiking neurons, chip-based platforms, reservoir computing and optical components. A small set of highly cited papers from the last decade, together with a few studies from neighboring fields, forms the knowledge base. This research offers a clear starting point for newcomers and helps identify areas of strength and potential new collaborations for funders and institutes. Limitations of this research include dependence on one database and a lack of keywords and addresses.

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I. INTRODUCTION

The application of artificial intelligence needs substantial computational capabilities. The majority of AI-based systems use electronic chips where there is a distinction between memory and computational resources. Hence, it becomes necessary for them to transfer information between each other, which makes the entire process more time-consuming and energy-intensive. It becomes increasingly important with the growing scale and complexity of AI algorithms (Li *et al*., 2021). One such computing approach that can be used is the photonic neuromorphic computing technology based on optical data processing.

An effective strategy would be the creation of computing systems modeled after the human brain. The human brain, though it uses minimal energy to function, is highly efficient at processing information thanks to a large number of neurons that are interlinked and work in parallel. A second suggestion is to use light instead of electricity. Light moves quickly and transmits multiple signals at once. Putting the two ideas together gives photonic neuromorphic computing, where light-based devices act as the neurons and the connections of a neural network (Shastri *et al*., 2021; Farmakidis *et al*., 2024). A neuron is a unit that adds up signals and fires a pulse when the total is large enough. On a chip, lasers and tiny channels for light do this job, and a network of them can learn to spot patterns in images or speech.

The field has moved quickly. Early laser-based devices were shown to fire short pulses much like nerve cells (Hurtado *et al*., 2010; Prucnal *et al*., 2016). Silicon chips were later built to carry out the matrix calculations at the heart of neural

networks (Shen *et al*., 2017; Tait *et al*., 2017). Other teams built networks that learn with light-based pulses (Feldmann *et al*., 2019) and fast chips for image-style calculations (Xu *et al*., 2021). Reservoir computing uses the natural behaviour of a laser or a loop of fibre as a ready-made network (Duport *et al*., 2012; Van der Sande *et al*., 2017). More recently, attention has turned to training such networks directly on the hardware (Hughes *et al*., 2018).

II. BACKGROUND AND RESEARCH GAP

A number of review articles have been done concerning this topic, which include the topics of photonic memory devices (Goi *et al*., 2020), optical neural networks (Liu *et al*., 2021), and the basic elements of neuron, synapse, and neural network (Guo *et al*., 2021). These reviews have offered good perspectives on the technological advancement in this field. However, the choice of focus and literature in these review articles may restrict them from giving an overview of the field as a whole. They cannot easily answer simple questions. How fast is the field growing? Which countries and teams lead it? Which topics belong together, and which are new? Scientometrics provides solutions to these queries through bibliometric mapping. For example, VOSviewer is employed for mapping the links between keywords, countries, and authors (van Eck & Waltman, 2010), whereas HistCite finds out the links between citations within selected literature (Garfield, 2009). According to Donthu *et al*. (2021), it is necessary to define clear search parameters and be open about all stages of the research process in bibliometric analysis. But no past research has employed such methods to analyse Web of Science records regarding photonic neuromorphic computing starting from the time when this field came into existence in the 1990s with the emergence of optical neural networks.

III. OBJECTIVES OF THE STUDY

1. To identify the growth in publications over time.
2. To identify the countries which are leaders in this field.
3. To identify the most productive and influential researchers.
4. To identify the main research trends and topics.
5. To identify the most cited studies and the basic knowledge base of the field.

IV. RESEARCH METHODOLOGY

A. Data Source

The data were collected from the Web of Science Core Collection using the Topic field (title, abstract, and keywords) in an advanced search. The Topic field search resulted in 1,481 articles, which covered the period from 1989 to 2026.

Search Strings

TS=("photonic neuromorphic comput" OR "neuromorphic photonic" OR "photonic neuromorphic" OR "neuromorphic optical comput*" OR "optical neuromorphic comput*" OR "neuromorphic optics" OR "photonic neural network*" OR "optical neural network*" OR "photonic neural comput*" OR "optical neural comput*" OR "photonic reservoir comput*" OR "optical reservoir comput*" OR "photonic reservoir network*" OR "optical reservoir network*" OR "photonic recurrent neural network*" OR "optical recurrent neural network*" OR "photonic spiking neural network*" OR "optical spiking neural network*" OR "photonic neural processor*" OR "optical neural processor*" OR ("photonic comput*" NEAR/5 neuromorphic) OR ("optical comput*" NEAR/5 neuromorphic).

B. Cleaning the Data

A total of 1481 records were kept. Of these, 1,332 are articles, 85 are reviews and 20 are conference papers. A small number of papers dated 2026 (34 records) count in the overall totals but are left out of the year-by-year trends, because that year was not complete. Spelling variants of keywords were merged, for example singular and plural forms and the short and long names of the same laser type. England, Scotland, Wales and Northern Ireland were combined as the United Kingdom in the tables. Country counts rely on the 1,390 records (94%) that carry author addresses, and keyword counts on the 848 records (57%) that carry author keywords.

C. Tools and Measures

Excel was used to clean the data and to build the tables and charts. HistCite was used to count citations in two ways: global citations, which are all citations recorded in Web of Science, and local citations, which count only citations from other papers in our dataset (Garfield, 2009). VOSviewer and biblioshiny were used to draw maps of countries, authors, journals and keywords (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010). Each country, author or keyword was counted once per paper. Keywords needed to appear at least five times to enter the keyword map, which gave 122 keywords. We also report citations per paper and the h-index, which is the largest number h such that h papers have at least h citations each (Hirsch, 2005).

Three further steps used the same data. First, to see how topics changed, we compared how often each keyword appeared in three periods (2015–2019, 2020–2022 and 2023–2025), as a share of the records that carry keywords. Second, for co-citation, we matched cited references by DOI, or by author, year, source, volume and page when no DOI was given. The 128 references cited at least 45 times were linked when they appeared together in the same reference list, and were grouped with the same community-detection method used for keywords. Third, to check whether differences in citations could be chance, we used the Mann–Whitney U test, which suits skewed counts, and we described growth with a straight-line fit to the logarithm of yearly papers.

Figure 1 shows the stages of the study in order from the search to the findings and which tool was used at each stage.

TABLE I OBJECTIVES, WHAT WAS MEASURED AND THE TOOL USED

Objective	What we measured	Tool
1. Growth over time	Papers per year, growth trend line, citations by period	Excel
2. Leading countries	Papers, citations, citations per paper, international co-authorship, Mann–Whitney tests	Excel, VOSviewer, Biblioshiny
3. Authors	Papers, citations, h-index, active years	Excel, HistCite, VOSviewer
4. Themes and clusters	Keyword frequency, keyword groups and change across periods	Excel, VOSviewer
5. Highly cited studies and knowledge base	Global and local citations; most cited references; co-citation groups; main journals	HistCite, Excel, VOSviewer

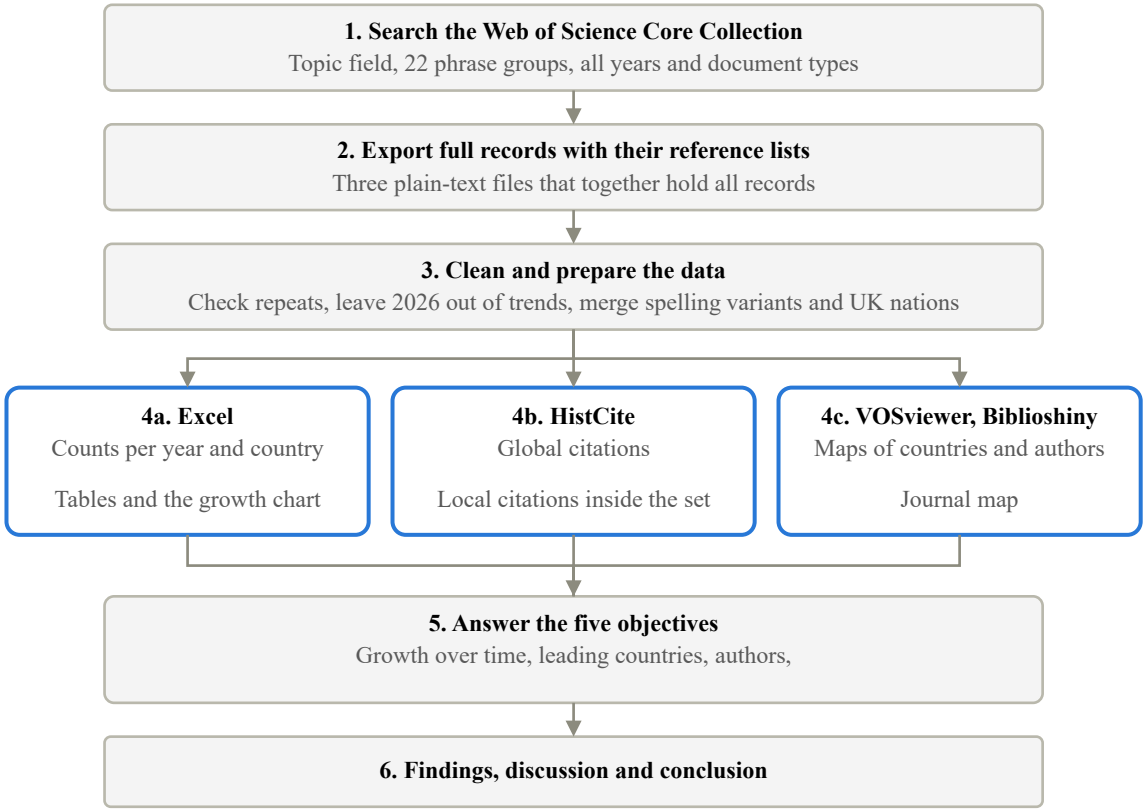


Fig.1 Workflow of the Study

V. FINDINGS

A. Growth of Publications

Figure 2 depicts the number of publications in each year from 1989 to 2025, while Table II illustrates the precise numbers along with the difference compared to the previous year. The annotated bars indicate the first peak as well as the beginning and end of the current increase trend. Studies in this area started out small in scope, with a handful of papers being published in 1989. Publications hit their first high point of 31 in 1996, after which there was less interest in research. Only 157 records fall in 1989–1999, and just 42 fall in the whole of 2000–2014, with many years showing one to four papers and two years showing none (Table III). Growth began again in 2016 and sped up after 2019, when 43 papers appeared. The count doubled to 88 in 2020 and reached 325 in 2025, which is 7.6 times the 2019 level, or about 40% more papers each year on average. About 80% of all records (1,192) were published between 2019 and 2025. Growth was not smooth: 2024 added only 3% over 2023, before 2025 rebounded by 38%. A further 34 records already carry a 2026 date.

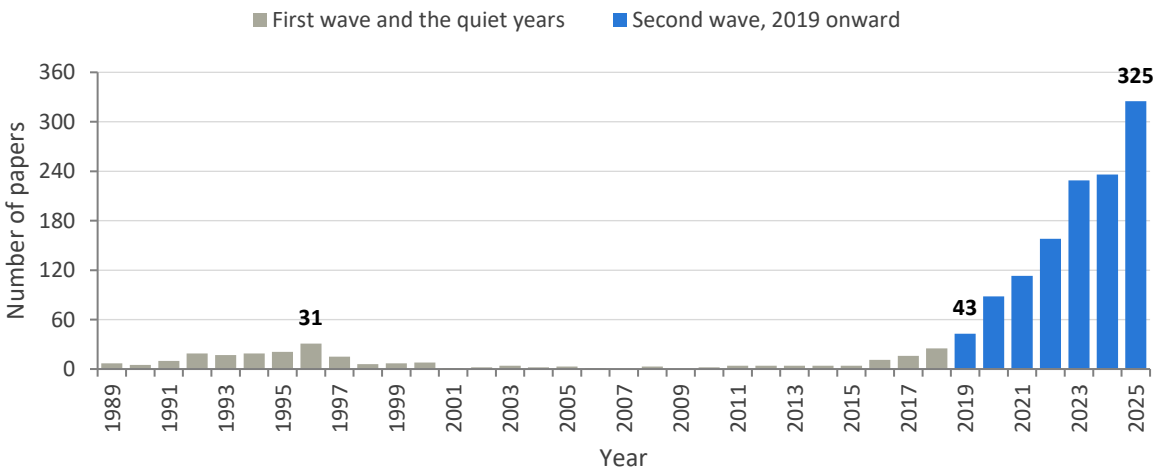


Fig.2 Number of Papers per Year, 1989–2025. Papers Dated 2026 are Not Shown Because that Year was Inadequate

TABLE II NUMBER OF PAPERS PER YEAR, 1989–2025, AND PERCENTAGE CHANGE FROM THE PREVIOUS YEAR (– WHERE THE PREVIOUS YEAR HAD NO PAPERS).

Year	Papers	Change (%)	Year	Papers	Change (%)	Year	Papers	Change (%)
1989	7	–	2002	2	+100	2015	4	0
1990	5	−29	2003	4	+100	2016	11	+175
1991	10	+100	2004	2	−50	2017	16	+45
1992	19	+90	2005	3	+50	2018	25	+56
1993	17	−11	2006	1	−67	2019	43	+72
1994	19	+12	2007	0	−100	2020	88	+105
1995	21	+11	2008	3	–	2021	113	+28
1996	31	+48	2009	0	−100	2022	158	+40
1997	15	−52	2010	2	–	2023	229	+45
1998	6	−60	2011	4	+100	2024	236	+3
1999	7	+17	2012	4	0	2025	325	+38
2000	8	+14	2013	4	0			
2001	1	−88	2014	4	0			
Total, 1989–2025: 1,447 papers (the 34 records dated 2026 are excluded)								

To describe the speed of growth, we fitted a straight line to the logarithm of yearly papers from 2015 to 2025. It gives average growth of about 53% a year (95% confidence range 43% to 64%), and the line explains 96% of the year-to-year variation. Grouping the years into periods shows a second pattern, which is how much attention each period's papers have received (Table III). Papers from 2015–2018 have been cited most per paper, with an average of about 170. This is partly because these papers include several landmark studies and have had the longest time to collect citations. The most recent period holds 790 papers, more than half the dataset, but each has so far been cited about 17 times on average because they are new.

TABLE III PAPERS AND CITATIONS BY PERIOD

Period	Papers	Share of all papers (%)	Average papers per year	Citations	Citations per paper
1989–1999	157	10.9	14	1,475	9.4
2000–2014	42	2.9	3	2,553	60.8
2015–2018	56	3.9	14	9,510	169.8
2019–2022	402	27.8	101	28,026	69.7
2023–2025	790	54.6	263	13,060	16.5
Total, 1989–2025	1,447	100	39	54,624	37.8

B. Leading Countries

Across the dataset, 1,390 records carry an address, and papers from China, the United States and the United Kingdom lead the counts (Table IV). China has by far the most papers, with 683, followed by the United States with 255. The picture shifts when citations are taken into account. The United States has the most total citations, whereas Canada, with fewer than one-tenth of China's publications, has the most citations per paper among the top ten. China's papers average 27 citations each, which is lower than for most Western countries. Part of this gap reflects age, because most Chinese papers are recent. Even when we compare only papers from 2019 to 2023, the average is about 46 for China, against 82 for the United States, 101 for the United Kingdom, 140 for Canada and 154 for Germany.

We also tested whether these differences could be chance. For papers from 2019 to 2023, the middle paper from China has 17.5 citations and the middle paper from the United States has 30. This difference is unlikely to be chance (Mann–Whitney test, $p < 0.001$; 294 and 157 papers). Papers with authors from more than one country also have more citations than papers from a single country (middle values of 29 and 19, $p < 0.001$; 176 and 453 papers). These tests show a link, not a cause: international papers may be cited more because stronger teams cooperate more.

TABLE IV TEN MOST PRODUCTIVE COUNTRIES

Country	Papers	Citations	Citations per paper	With international co-authors (%)
China	683	18,649	27.3	18
United States	255	19,997	78.4	42
United Kingdom	96	6,265	65.3	73
Canada	70	9,739	139.1	79
Japan	68	1,944	28.6	15
Belgium	62	3,742	60.4	35
France	51	3,344	65.6	73
Germany	50	4,348	87.0	70
Greece	48	1,210	25.2	56
Spain	43	3,319	77.2	74

Leadership has also changed over time. In the 1990s, Japan (15 papers), China (13) and the United States (11) were close. Between 2015 and 2019 the United States led with 28 papers, ahead of China with 20 and Belgium with 17. Since 2020, China has pulled far ahead, with 627 papers against 206 for the United States. China's share of each year's papers rose from 21% in 2019 to 39% in 2020 and 62% in 2025. Cooperation across borders differs a lot between countries. Only 316 of the 1,390 records with addresses (23%) involve more than one country. Canada, Spain, the United Kingdom, France and Germany work with foreign partners on 70% or more of their papers, while China and Japan do so on fewer than one in five. The strongest partnerships are China and the United States (39 papers), Canada and the United States (36), China and the United Kingdom (24), Canada and China (23), Australia and China (22), and China and Singapore (21). Figure 3 shows the biblioshiny country map, in which dark colors stand for countries with more papers and links show cooperation between countries.

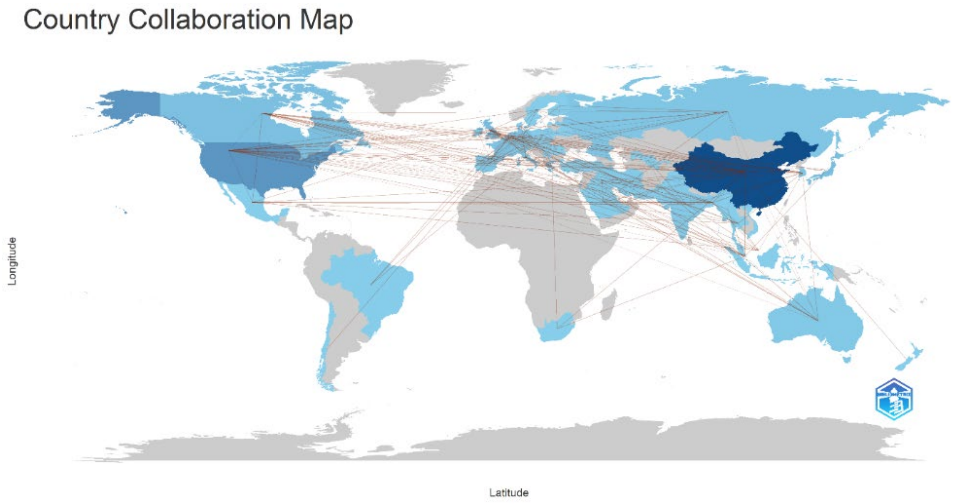


Fig.3 Country Map Drawn in Bibliometrix (biblioshiny).

C. Productive and Influential Authors

Authors were matched by full name so that people with the same short name are not merged. The most productive authors are mostly from one place, Xidian University in China (Table V). Hao Yue leads with 64 papers, followed by Xiang Shuiying with 63, and Zhang Yahui and Guo Xingxing with 45 and 42. Together these four and Han Yanan wrote 73 papers in the dataset, and nearly all of them (66) deal with lasers or spiking neurons. Their influence, measured by citations, is moderate. The most cited authors are a different group. Paul Prucnal (Princeton University), Bhavin Shastri (Queen's University) and Alexander Tait (Princeton) each have more than 4,300 citations and the highest h-index values, 22 and 19, from far fewer papers. Their 43 joint papers mostly deal with silicon chips, microrings and weight banks. Peter Bienstman (Ghent University) is the most productive European author, with 30 papers, and 27 of them involve reservoir computing. Two authors stand out for citations without being frequent authors in the set: Dirk Englund (4,147 citations from 13 papers) and Marin Soljacic (3,260 from just two papers).

Figure 4 shows the author map from VOSviewer, coloured by the average year of each author's papers. It makes the difference between long-standing and recent contributors easy to see.

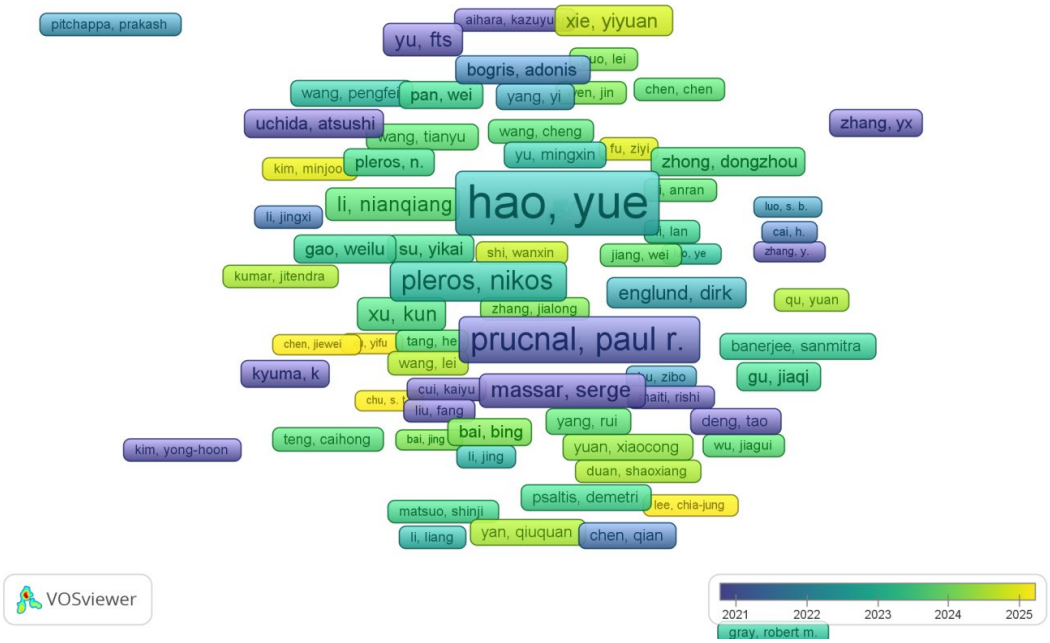


Fig.4 Author Map Drawn in Vosviewer, Colored by Average Publication Year (2021–2025).

TABLE V MOST PRODUCTIVE AUTHORS

Author	Main affiliation	Papers	Citations	h-index	Active years
Hao Yue	Xidian University	64	1,493	21	2018–2026
Xiang Shuiying	Xidian University	63	1,378	20	2016–2026
Zhang Yahui	Xidian University	45	1,146	18	2018–2025
Guo Xingxing	Xidian University	42	1,013	17	2018–2025
Prucnal Paul R.	Princeton University	35	4,667	22	2017–2025
Shastri Bhavin J.	Queen's University	35	4,613	22	2017–2025
Han Yanan	Xidian University	33	622	13	2018–2026
Bienstman Peter	Ghent University	30	1,380	17	2008–2025
Hurtado Antonio	University of Strathclyde	24	937	15	2015–2025
Huang Chaoran	Chinese University of Hong Kong	24	1,328	17	2018–2025
Pleros Nikos	Aristotle University of Thessaloniki	23	675	15	2020–2026
Tait Alexander N.	Princeton University	22	4,330	19	2017–2024

D. Research Themes and Topic Clusters

The most common author keywords are optical neural network 250 records, optical computing 104, photonics (81), photonic neuromorphic computing (71), silicon photonics (69), photonic neural network (67), reservoir computing (63), neural network (63), neuromorphic computing (54) and deep learning (49). A map of keywords that appear together comprises 122 keywords with at least five occurrences, joined by 1,902 links, and falls into five clusters Table VI. These groups were found with a standard community-detection method, so VOSviewer may draw some borders slightly differently.

TABLE VI KEYWORD CLUSTERS

Cluster	Keywords	Examples	What it covers
Optical neural networks and deep learning	28	optical neural network, optical computing, deep learning, diffractive neural network, image classification, inverse design, nanophotonics	Light-based networks that run deep-learning tasks, often on images
Spiking neurons and laser hardware	26	photonic neuromorphic computing, VCSEL, spiking neural network, neurons, pattern recognition, optical pulses	Lasers that fire pulses like nerve cells
Chip-based platforms and materials	22	silicon photonics, photonic neural network, neuromorphic computing, machine learning, phase change materials, graphene	Integrated chips and new materials for photonic networks
Reservoir computing	25	reservoir computing, optical feedback, semiconductor lasers, nonlinear dynamics, optical fibres, recurrent neural network	Using the natural behaviour of lasers and fibre loops as networks
Optical components and signal processing	21	neural network, nonlinear optics, waveguides, optical signal processing, interferometry, resonators	Building blocks and signal-handling tasks

Keyword use has also shifted (Table VII). Among records with keywords, "optical neural network" rose from about 7% of records in 2015–2019 to about 25% in both later periods. "Reservoir computing" fell from about 21% to about 7% of records, even though its count rose from 9 to 33 records, so it kept growing but more slowly than the field as a whole. Terms like artificial intelligence, optical imaging, and training did not appear during the 2015-2019 period but appeared more frequently in later periods. Nevertheless, the results for the first period have to be viewed with caution since 42 out of the total number of papers included keywords.

TABLE VII SHARE OF RECORDS USING EACH KEYWORD

Keyword	2015–2019 (42 records)	2020–2022 (200 records)	2023–2025 (475 records)
optical neural network	7.1	25.5	24.8
optical computing	9.5	11.5	13.1
photonic neural network	7.1	10.0	9.1
silicon photonics	11.9	9.5	9.3
neuromorphic computing	14.3	12.0	4.6
photonic neuromorphic computing	14.3	13.0	7.4
reservoir computing	21.4	8.0	6.9
deep learning	7.1	10.0	5.3
artificial intelligence	0.0	6.5	5.3
optical imaging	0.0	4.0	3.4
spiking neural network	0.0	2.0	2.3

E. Most Cited Papers

There were 119 papers with a citation score greater than 100 and 112 papers with no citations at all. Table VIII shows the top ten most-cited papers in the Web of Science database by global and local citations. The two measures tell different stories. Shen *et al*. (2017) lead on both, with 2,833 global and 590 local citations. Shastri *et al*. (2021), Feldmann *et al*. (2019), Xu *et al*. (2021), Tait *et al*. (2017) and Zhang *et al*. (2021) are all widely cited in the field. In contrast, the papers on microwave photonics (Marpaung *et al*., 2019), oxide-based devices (Lee *et al*., 2017) and hardware neural networks (Misra & Saha, 2010) have many global citations but are rarely cited here (17, 25 and 20 times). They match the search terms, yet they belong to neighbouring fields and are not part of the field's core.

TABLE VIII TEN MOST CITED PAPERS IN THE DATASET

First author, year, journal	Topic	Global citations	Local citations
Shen 2017, Nature Photonics	Deep learning on a coherent nanophotonic chip	2,833	590
Shastri 2021, Nature Photonics	Review of photonics for AI and neuromorphic computing	1,684	302
Feldmann 2019, Nature	Self-learning all-optical spiking network	1,348	374
Marpaung 2019, Nature Photonics	Review of integrated microwave photonics	1,189	17
Xu 2021, Nature	Photonic convolutional accelerator	1,047	249
Tait 2017, Scientific Reports	Silicon weight banks for neuromorphic photonic networks	766	218
Zhang 2021, Nature Communications	Optical neural chip for complex-valued networks	605	166
Lee 2017, Advanced Materials	Oxide-semiconductor photonic synapse devices	554	25
Van der Sande 2017, Nanophotonics	Review of photonic reservoir computing	518	97
Misra 2010, Neurocomputing	Survey of neural networks in hardware	511	20

The knowledge base is the set of works that the papers in the dataset cite most in their own reference lists (Table IX). It combines the field's own landmark papers with a few outside works. The diffractive deep neural network paper (Lin *et al*., 2018), the photonic tensor core paper (Feldmann *et al*., 2021) and the general deep learning review (LeCun *et al*., 2015) come from outside our dataset but are cited by hundreds of papers within it. Reservoir computing has its own foundations, in the papers by Appeltant *et al*. (2011) and Vandoorne *et al*. (2014). Most of the knowledge base dates from 2017 onwards, which agrees with the recent surge in output. Figure 5 shows the journals that carry this work. Nature Communications, Nature Photonics, Optica, Nanophotonics and Scientific Reports are among the most prominent, together with several specialist photonics titles.

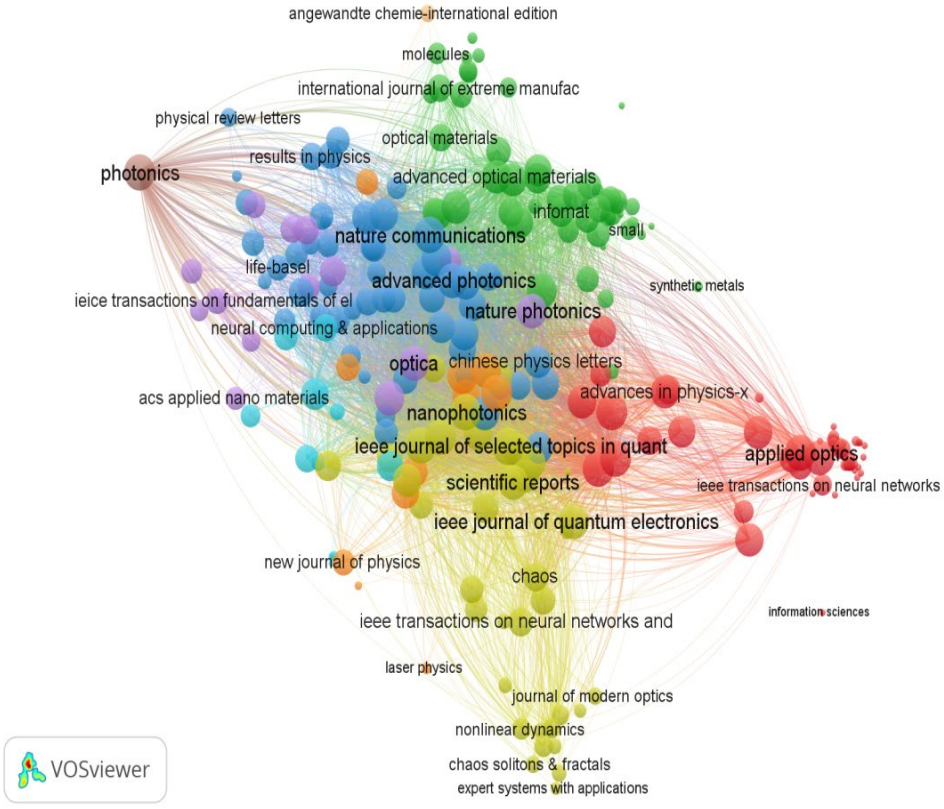


Fig.5 Journal Map Drawn in VOSviewer

TABLE IX TEN MOST CITED REFERENCES (THE KNOWLEDGE BASE)

Reference	Topic	Times cited by dataset papers
Shen 2017, Nature Photonics	Coherent nanophotonic deep learning	590
Lin 2018, Science	Diffractive deep neural networks	384
Feldmann 2019, Nature	All-optical spiking network	374
Shastri 2021, Nature Photonics	Review of photonics for AI	302
Feldmann 2021, Nature	Photonic tensor core	295
Xu 2021, Nature	Photonic convolutional accelerator	249
Tait 2017, Scientific Reports	Silicon weight banks	218
LeCun 2015, Nature	Deep learning review	201
Appeltant 2011, Nature Communications	Reservoir computing with one node	182
Vandoorne 2014, Nature Communications	Reservoir computing on a silicon chip	171

A co-citation analysis links references that appear together in the same paper's reference list. We used the 128 references cited at least 45 times, and they fall into three groups (Table X). The largest contains 63 references on optical neural networks, diffractive networks and deep learning. The second holds 39 references on neuromorphic photonic hardware and spiking neurons. The third holds 26 references on reservoir computing. The three groups match the keyword clusters, which gives more confidence that the structure is real and not an effect of one method. The first group is the largest, which agrees with the rise of optical neural networks in recent years.

TABLE X CO-CITATION GROUPS AMONG THE 128 MOST CITED REFERENCES

Group	References	Leading members	What it covers
Optical neural networks and deep learning	63	Shen *et al*. (2017); Lin *et al*. (2018); Shastri *et al*. (2021); Feldmann *et al*. (2021); Xu *et al*. (2021); LeCun *et al*. (2015)	Light-based networks, diffractive networks and deep learning
Neuromorphic photonic hardware and spiking neurons	39	Feldmann *et al*. (2019); Tait *et al*. (2017); Prucnal *et al*. (2016)	Weight banks, spiking lasers and brain-like chips
Reservoir computing	26	Appeltant *et al*. (2011); Vandoorne *et al*. (2014); Duport *et al*. (2012)	Using lasers and delay loops as ready-made networks

VI. DISCUSSION

Two rounds of research, not constant advancement (Objective 1). The graph indicates two peaks of research on optical neural networks, one in the 1990s and another since 2019, with a long period of poor output in between. Initial research was based on big bulky elements like holograms, liquid crystal displays, and photo-sensitive crystals. The new wave is chip-based. The articles that revived the extent between 2017 and 2019 are now among the most cited (Shen *et al*., 2017; Tait *et al*., 2017; Feldmann *et al*., 2019). They reveal the basic components: programmable circuits on silicon, light-based pulses, and fast matrix calculations. Our statistics reveal the drop after the 1990s, but not the cause, and determining the reasons would necessitate a different type of investigation. The slower growth in 2024 indicates the intensification is not certain to be smooth.

A large producer and a highly influential group of countries (Objective 2). Since 2020, China has produced the majority of papers, with its share increasing year after year. Chinese articles are typically authored without foreign co-authors, whereas Canada, the United Kingdom, France, Spain, and Germany use cross-border teams. Papers from the United States, Canada, and Germany receive more citations per paper. Much of the difference with China is due to age, as Chinese papers are fresher, but it persists when papers from the same years are compared. The image should be reviewed again in a few years, after current studies have had a chance to be referenced. Citations are likewise concentrated: the most cited paper receives around 5% of all citations in the dataset.

Volume and influence are distinct concepts (Objective 3). The most active authors collaborate at Xidian University, mostly on laser-based spiking neurons. The most cited writers, from Princeton and Queen's University, have produced fewer articles yet are associated with the works that the field cites the most. This trend demonstrates that there are two types of research leadership: contributions from established research teams and the impact of a few highly cited early works. The University of Ghent has made significant contributions to reservoir computing. However, the citation counts of Dirk Englund and Marin Soljačić highlight the impact of a few prominent works on author citations.

Five themes with three main directions (Objective 4). The five keyword clusters line up with three main directions. The first makes use of light-based component networks to speed up calculation and imaging. The second is reservoir computing, which uses the natural behaviour of a laser with delayed feedback instead of building every connection. The

third uses lasers and resonators as spiking neurons. Chip platforms and optical components support all three. Recent work continues each direction: chips that handle several data dimensions at once (Dong *et al*., 2023), accelerators that reach trillions of operations a second (Bai *et al*., 2025), reservoir systems for speech (Picco *et al*., 2025), resonator-based neurons on silicon (Tamura *et al*., 2024), links to fibre communication (Huang *et al*., 2021) and laser chips that act as spiking neurons (Xiang *et al*., 2023). Many of these topics revolve around energy conservation, which was the field's primary purpose (Li *et al*., 2021).

Changes in the importance of research themes (Objective 4). Optical neural networks surged in importance, accounting for around one-quarter of all articles including keywords and became the most common study theme. Reservoir computing decreased its market share to less than 10% (from approx. 20%) and slowed down compared to the general field. The terms associated with artificial intelligence, imaging or training only appear after 2019 highlighting the movement towards practical applications. The data between 2015-2019 is based on few records and thus should be taken as a general trend. A knowledge base with some external assistance (Objective 5). The field is based on a small number of significant publications published between 2017 and 2021, as well as work from related topics such as general deep learning. A few publications with high global citations are only loosely connected, demonstrating that keyword-based searches also include work from surrounding areas. Comparing global and local citations is an easy approach to tell them apart.

Co-citation tells the same tale from a different perspective. The references given combined fall into three categories: optical neural networks and deep learning, neuromorphic photonic hardware and spiking neurons, and reservoir computing. These match the keyword groupings, indicating that two separate approaches point to the same structure. Applications of these results. New researchers can begin by reviewing the highly cited publications in Section 5.5, as well as the five keyword groupings. Funders and institutions can observe which regions excel in various directions. Authors seeking partners should be aware that the United States, Canada, and the United Kingdom have the strongest international linkages, whereas China's links abroad are fewer than its size would suggest.

VII. LIMITATIONS

The study uses Web of Science database. Other sources, such as Scopus, would produce different results, while conference papers and patents are only partially covered.

VIII. CONCLUSION

Research on photonic neuromorphic computing has expanded from a few early experiments in the 1990s to a huge field with hundreds of articles published each year. Following a long quiet period, growth resumed in 2016 and accelerated dramatically around 2019. China produces most of the papers, led by a single group of authors at Xidian University, while the United States, Canada and several European countries produce papers with higher average citations and more international teamwork. A small number of authors from Princeton, Queen's University, Ghent and elsewhere carry the most influence. The keywords fall into five distinct categories, with optical neural networks gaining the most traction in recent years. The field is based on a small number of significant studies, largely from 2017, organized into three co-citation groups: optical neural networks, neuromorphic hardware, and reservoir computing. Newer publications have had little time to be cited; therefore the current disparity in influence may diminish. Future research could analyze other databases, including patents, and see whether the groups remain stable. Overall, the field is young, quick, and still developing. This study provides a clear starting point for newcomers while also assisting funders and researchers in identifying areas of strength and collaboration.

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