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Applications of Analytics in Delivery: A Bibliometric Study, 2014-2026

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ABSTRACT: Analytics now shapes how hospitals treat patients, how medicines reach the right cells, and how parcels, power and online courses reach their users. This study maps the research that links delivery and analytics. We searched the Scopus database with the query "Delivery AND Analytics" and, after screening, kept 2,802 journal documents (2,195 articles and 607 reviews) published between 2014 and 2027. Biblioshiny (Bibliometrix) and VOSviewer were used to study publication and citation trends, leading authors, sources and countries, and the keyword structure of the field. Output grew from 52 papers in 2014 to 544 in 2026, about 21.6 per cent a year, and 2025 and 2026 together hold 38.4 per cent of all documents. Health care dominates: about six in ten documents deal with patients, hospitals or clinical care, and "health care delivery" is the most frequent subject term once generic indexing labels are set aside. The keyword maps show four groups: health-care delivery and management, analytics methods and digital technology, clinical study terms, and drug delivery with precision medicine. Logistics and last-mile delivery form a smaller strand that is growing quickly. The paper also reports the limits of the data. The export has no cited references, so co-citation and bibliographic coupling could not be run, and the word "delivery" covers very different subjects, such as parcel routing and nanoparticle drug carriers.

KEYWORDS: Delivery; Analytics; Bibliometric analysis; Health care delivery; Last-mile logistics; Scopus; VOSviewer; Biblioshiny.

1. INTRODUCTION

The word "delivery" means different things in different fields. A hospital manager thinks of care delivery, a pharmacologist of drug delivery, a logistics planner of the last mile to a customer's door, and a teacher of how a course is delivered. These groups now share one habit: they use data to decide what to deliver, when, and to whom.

Analytics is the use of data, statistics and computer models to describe what happened, predict what will happen and suggest what to do next (Wang et al., 2019). Health care took up these tools early. Electronic health records made large amounts of clinical data available, and studies published in 2014 already showed how analytics could flag high-cost patients, predict readmissions and support a learning health system (Bates et al., 2014; Krumholz, 2014). Since then, machine learning and artificial intelligence have moved into diagnosis, remote monitoring and conversational agents (Jiang et al., 2017; Milne-Ives et al., 2020).

The same ideas appear in logistics. Delivery firms use travel-time predictions, forecasts of when customers are at home, and parcel locker data to plan the last mile (Liu et al., 2021; Kandula et al., 2021; Lyu & Teo, 2022). Power utilities analyse smart meter data to manage the delivery side of the grid (Wang et al., 2019), and universities use learning analytics to adjust how courses are delivered (de Barba et al., 2016; Wong & Li, 2020).

A narrative review cannot easily cover a body of work this wide. Bibliometric methods count publications and citations, map who works with whom, and group keywords into themes. This shows where the work is concentrated and where it is thin (Donthu et al., 2021; Zupic & Čater, 2015). This paper applies those methods to the research that joins delivery and analytics.

The records come from Scopus for the query "Delivery AND Analytics". After screening, 2,802 documents remain: 2,195 articles and 607 reviews from 1,634 sources and 12,328 authors, published between 2014 and 2027. Two of these records carry the year 2027. They are early-access items. We kept them so that the data set matches the screening flow, but we report growth for 2014 to 2026 and treat 2026 as a partial year.

Two limits shape what follows. First, the Scopus export holds no cited-reference data, so co-citation and bibliographic coupling are not possible. The analysis therefore rests on publication and citation counts, on author, source and country output, and on keywords. Second, the search is broad. It brings hospital management, nanomedicine, parcel routing, smart grids and online learning together under one label. We treat this spread as a finding and report it openly.

The paper has three aims: to describe the growth, citation pattern, leading authors, sources and countries of delivery and analytics research in Scopus; to map its main themes through keyword co-occurrence and link them to the strands found in the literature; and to state the gaps and data limits that follow from the search. These aims lead to four questions:

RQ1: What are the publication and citation trends between 2014 and 2026, and how concentrated is citation impact?

RQ2: Which countries, authors and sources produce most of the work, and what does the pattern of collaboration show?

RQ3: Which themes appear in the keyword co-occurrence maps, and in which fields of delivery is analytics used most?

RQ4: Which limits in the data and the search strategy constrain the conclusions, and how should later studies on this topic be designed?

The rest of the paper sets out the method, reviews the literature by field of application, reports the bibliometric results, proposes a research agenda, and closes with the conclusions and limits of the study.

2. RESEARCH METHODOLOGY

The final set of 2,802 documents (2,195 articles and 607 reviews) is analysed with bibliometric methods to trace how research on delivery and analytics has grown and how its themes are organised. Bibliometric analysis suits this purpose because it handles a large body of literature through counts and maps instead of a reading of each paper. Donthu et al. (2021) describe it as a way to study both the performance and the thematic structure of a research field, and Zupic and Čater (2015) note that it gives a systematic and repeatable view of how a field is organised.

Article Selection and Inclusion and Exclusion Criteria

The Scopus database was searched on 11 September 2026 with the query "Delivery AND Analytics", and the records were exported the same day. Scopus was chosen because it indexes a large multidisciplinary set of journals and supplies the bibliographic and citation data that bibliometric tools need (Pranckutė, 2021). The first search returned 6,283 records. These were filtered by publication period, document type, duplicates, language and source type, in line with common practice for systematic reviews in operations management (Thomé et al., 2016).

The time filter kept records from 2014 to 2027 and removed 200, leaving 6,083. Keeping only articles and reviews removed a further 3,203 records and left 2,880. Removing 8 duplicates left 2,872, the English-language filter removed 42 and left 2,830, and the journal filter removed 28 records from other source types. The final set has 2,802 documents.

Two records in this set are dated 2027. Both are early-access papers. We kept them so that the analysis matches the screening flow, but they distort one figure. Biblioshiny computes the annual growth rate from the first and the last year, and with only two documents in 2027 it reports a growth rate of -22.17 per cent. Section 4 reports the growth rate for 2014 to 2026 alongside it.

Figure 1 shows the screening steps as a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram.

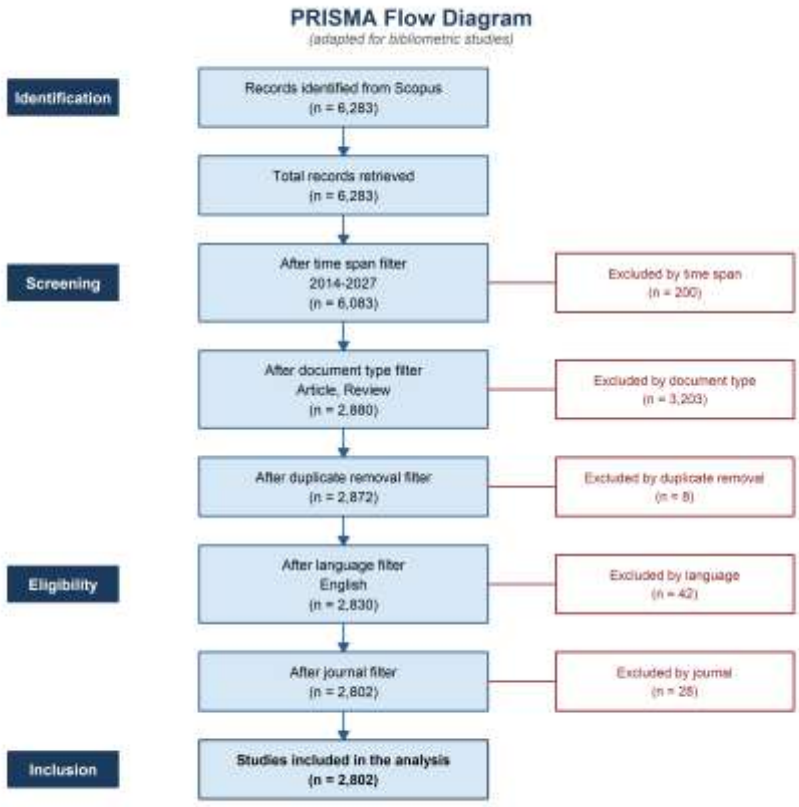


Figure 1. Record screening flow of the Scopus search, adapted from the PRISMA framework.

Bibliometric Analysis

The analysis covers publication trends, citations, productive authors, journals and countries, keywords and collaboration. Citation analysis counts how often a paper is cited and shows which authors, countries and documents draw the most attention (Donthu et al., 2021). Co-word analysis looks at which keywords appear together in the same papers and builds a map of topics from them. Co-authorship and country data show who works with whom.

Two tools were used. Bibliometrix, with its web interface Biblioshiny, is an R package for science mapping (Aria & Cuccurullo, 2017). It produced the main information table, the annual production series, the author and country counts, the thematic map and the input for the three-field plot. VOSviewer builds and draws keyword networks and groups related terms into clusters (van Eck & Waltman, 2010). Microsoft Excel was used to arrange the exported tables. A few figures that Biblioshiny does not report directly, such as citation medians, multi-country papers and the share of records in each field of application, were computed from the Bibliometrix export file.

3. LITERATURE REVIEW

Delivery, in the broad sense used here, is the step where a service or product reaches the person who needs it. Analytics enters that step when data are used to decide how the delivery should happen. The records in this study apply the idea in very different settings, so the review is organised by field of application rather than by method.

The data set holds 2,802 documents with 73,783 Scopus citations between them. The mean is 26.33 citations per document but the median is only 7, so a small number of papers draw most of the attention. A word search of titles, abstracts and keywords gives a rough idea of where the work sits. About 61 per cent of documents mention patients, hospitals, clinics or other health terms, about 20 per cent mention education or students, about 14 per cent deal with logistics, supply chains or e-commerce delivery, and about 9 per cent with drug delivery. Smaller shares cover energy, public services and software delivery. These groups overlap and the figures are only a guide, but they explain why health care takes up most of this review.

The papers below were chosen to illustrate each strand, usually from among the most cited in their area. The export has no cited-reference data, so we could not use a citation network to pick them. The selection reflects our judgement, and other relevant studies may have been left out.

1. Big Data and Analytics in Health-Care Delivery

The oldest well-cited strand treats analytics as a tool for running health systems better. In a 2014 issue of Health Affairs, Bates et al. (2014) described six uses of clinical analytics that could cut costs: high-cost patients, readmissions, triage, patients whose condition worsens, adverse events, and treatment of diseases that affect several organ systems. In the same issue, Krumholz (2014) argued that large health data sets could feed a learning health system, but only with new thinking, training and tools. Fihn et al. (2014) described how the US Veterans Health Administration built a national data warehouse on a shared electronic health record and used it to monitor medication and predict the risk of poor outcomes.

Reviews that followed sorted the field into areas of use. Belle et al. (2015) looked at image, signal and genomic analytics and at the problems of combining data from different sources. Kohli and Tan (2016) named integration and analytics as the two areas where information systems research could improve care delivery through electronic health records. Kamble et al. (2019) classified 91 papers into general health care, clinical diagnosis and research, service delivery, disease transmission and health insurance. Khanra et al. (2020) grouped 41 studies into five perspectives, including hospital management and technology in service delivery. Shen et al. (2025) traced 25 years of electronic health records in medical research. They found that these records, now used with artificial intelligence and big data analytics, have become central to patient care, public health surveillance and medical research.

Together these papers set the questions that later work keeps returning to: which patients need attention first, how routine records can be used, and how new tools fit into clinical workflow.

2. Artificial Intelligence, Remote Care and Precision Medicine

The most cited document in the data set, with 3,932 citations, is a review of artificial intelligence in health care by Jiang et al. (2017). It describes machine learning for structured data and natural language processing for text, and reviews uses in stroke care for early detection, treatment and outcome prediction. Later reviews look at narrower tasks. Khalifa and Albadawy (2024) reviewed 30 studies on artificial intelligence in diagnostic imaging and grouped its gains into four domains, among them image analysis, operational efficiency, and predictive and personalised care. Milne-Ives et al. (2020) assessed conversational agents in health care, which support behaviour change, treatment, monitoring, triage and screening.

Care delivery is also moving out of the hospital. Yetisen et al. (2018) reviewed wearable devices that monitor vital signs, together with stimuli-responsive materials for drug delivery. Loncar-Turukalo et al. (2019) found that wider use of wearables for connected health is still held back, and studied the literature through technology, safety and security, and user concerns. During the COVID-19 pandemic, Firouzi et al. (2021) described how the Internet of Things, artificial intelligence, robotics and blockchain were used for tracking and tracing, remote patient monitoring, and diagnosis and prognosis.

Precision medicine adds another layer. Ginsburg and Phillips (2018) noted that the discovery of disease-related genetic variants has moved faster than its use in clinics, and argued that data science and analytics are needed for health systems that do research as part of everyday care. Meder et al. (2025) applied similar ideas at population level and showed how artificial intelligence can find disease patterns and guide resource allocation in cardiovascular care. The newest work concerns large language models. Gencer and Gencer (2025) mapped more than 500 papers on these models in health care, published between 2021 and 2024, and found the United States, Germany and the United Kingdom to be the main contributors.

3. Drug Delivery and Nanomedicine

A second meaning of delivery in the data set is drug delivery: getting a medicine to the right part of the body in the right dose. Here "analytics" often refers to laboratory and analytical chemistry methods rather than business data. Hwang et al. (2020), with 660 citations, reviewed polymeric micelles that carry poorly soluble drugs and the analytical methods used to study what happens inside them. Egorova et al. (2017) reviewed the biological activity of ionic liquids and their possible use in drug synthesis and drug delivery systems.

Data analytics in the computing sense is entering this area too. Chen et al. (2022) argued that nanomedicine design is still mostly trial and error and that machine learning could predict how nanomaterials behave, provided researchers first curate and standardise their data. Samathoti et al. (2025) reviewed how nanoparticles for targeted drug delivery and artificial intelligence for early detection and predictive analytics might be combined in cancer care. This strand is recent. Records indexed under "drug delivery system" have a mean publication year of 2023.3, later than the main health-care delivery terms.

4. Last-Mile Logistics and Supply Chain Delivery

In logistics, delivery means moving goods to customers, and analytics is used to plan routes, assign orders and forecast demand. Liu et al. (2021) used data from a food delivery service to combine travel-time predictions with order assignment. They found that learning how drivers actually behave matters, and that a larger sample does not make up for a wrong model of driver routing. Kandula et al. (2021) used machine learning to predict when e-commerce orders could be delivered successfully and fed these predictions into delivery schedules. On two real data sets the approach saved up to 10.2 per cent of delivery costs. Lyu and Teo (2022) used locker usage data from a courier company to plan a shared network of public parcel lockers in Singapore.

Reviews place this work in a wider frame. Giuffrida et al. (2022) reviewed optimisation and machine learning for last-mile logistics and linked the rise of e-commerce to traffic, pollution and the use of public space in cities. Demir et al. (2022) discussed drones, delivery robots, pickup points and collaborative logistics alongside the vehicle routing problem. Shuaibu et al. (2025) reviewed artificial intelligence, Internet of Things monitoring and hybrid networks of drones, ground robots and vans. Customer-facing studies also appear. Cheng et al. (2021) used internet data to build a service quality scale for online food delivery and found that reliability, assurance and system operation raise customer satisfaction.

Further up the chain, Lee (2017) proposed a genetic algorithm that uses purchase predictions to send products to a nearby distribution centre before the customer orders, an approach called anticipatory shipping. Cavalcante et al. (2019) combined machine learning and simulation to select resilient suppliers, using on-time delivery as the measure of reliability. Chae (2015) analysed 22,399 tweets tagged #supplychain, some of which carried strong views about companies' delivery services. Zhong et al. (2017) studied RFID data on a manufacturing shop floor and found that one buffer took up 40.57 per cent of total delivery time. Pasupuleti et al. (2024) reported that machine learning improved demand forecasting accuracy by 15 per cent for a multinational retailer.

Health care meets logistics in studies of medicine supply. Bag et al. (2023) studied big data and artificial intelligence platforms in health-care supply chains in South Africa, and Arji et al. (2023) reviewed the digital tools used to keep these supply chains working during COVID-19. Prasad et al. (2018) showed how big data relates to the delivery of humanitarian services by non-governmental organisations.

5. Energy, Cities, Public Services and Education

Power and data networks are a third setting. Wang et al. (2019), the third most cited document in the set, reviewed smart meter analytics in three stages (descriptive, predictive and prescriptive) and three uses: load analysis, load forecasting and load management. Ahmad et al. (2022) reviewed machine learning for energy distribution, including price forecasting and cyber security for power delivery. Bibri (2018) looked at how sensor data from the Internet of Things could support service delivery in sustainable cities. Zhang and Letaief (2020) described edge computing for connected vehicles, where storage and processing close to the user allow low-delay content delivery.

Governments use the same tools to deliver public services. Chatfield and Reddick (2018) studied Houston's 311 on-demand service and found that some departments used big data analytics to respond faster to citizens, but that city-wide change had not happened. Osman et al. (2019) proposed a cognitive analytics framework, based on data envelopment analysis and classification trees, to improve electronic government services in Turkey. Löfgren and Webster (2020) discussed what big data adds to public service delivery, along with problems of data quality, ownership and privacy.

In education, learning analytics studies how online behaviour relates to results. De Barba et al. (2016) found that participation was the strongest predictor of performance in a massive open online course, followed by motivation. Joksimović et al. (2015) analysed 204 offerings of 29 courses and found that time spent on student-system interaction had a steady positive effect on final grades. Wong and Li (2020) reviewed 24 cases of analytics-based intervention in

higher education, most aimed at study performance, personalised feedback and retention. In business and software teams, Larson and Chang (2016) traced how agile methods changed the delivery of business intelligence, and Snyder and Curtis (2017) showed how analytics guided Fannie Mae's move to agile and DevOps, with an average 38 per cent gain in structural quality and a 28 per cent rise in productivity.

6. Ethics, Privacy and Fairness

Several well-cited papers warn about the costs of analytics in delivery. Cohen et al. (2014) set out the legal and ethical issues at each of the four stages of a predictive model's life, from data collection through testing to wider use, and recommended that patients take part in model governance from the start. Yao et al. (2022) found that digital health technologies, meant to make care delivery more efficient, have also produced inequities between groups of citizens. Thomasian et al. (2021) argued that bias in health-care artificial intelligence needs regulation at each phase of the algorithm life cycle. On the technical side, Froelicher et al. (2021) built a federated analytics system that lets several institutions analyse their patient data together without revealing it, and used it to reproduce two published studies. Saheb et al. (2021) mapped research on the ethics of artificial intelligence in health care with bibliometric and content analysis and listed 40 research gaps.

Three points come out of this review. First, health care is the core of the field, and the agenda set out in 2014 (high-risk patients, readmissions, electronic records) still frames much later work. Second, the methods have shifted from big data and descriptive reporting towards machine learning, prediction and, since 2024, large language models. Third, the word "delivery" links fields that have little else in common. Hospital managers, pharmacologists, logistics planners, energy engineers and teachers use similar tools but publish in separate journals. The bibliometric results in the next section test these points against the data.

4. DATA ANALYSIS AND RESULTS

This section reports the performance of the data set and the structure of its keyword network. The screening steps and PRISMA counts are given in Section 2. All tables use the Biblioshiny export of the 2,802 screened documents (Scopus export of 11 September 2026), and the interpretation is limited to this export.

Main Information about the Data

Table 1 follows the usual order of a bibliometric study, with performance analysis before science mapping (Donthu et al., 2021; Aria & Cuccurullo, 2017). Co-citation and bibliographic coupling could not be run because the cited-reference field is empty for every record. The set holds 2,802 English-language documents from 1,634 sources written by 12,328 authors: 2,195 articles and 607 reviews. Reviews make up 21.7 per cent of the set, and 72 records were still marked as articles in press (18 from 2025, 51 from 2026 and 3 from earlier years).

With 1.71 documents per source, the journal base is very spread out. The most frequent source, the Journal of Medical Internet Research, has only 42 documents (1.5 per cent), followed by IEEE Access (35) and Scientific Reports (24). Teams are fairly large. The average document has 4.99 authors, only 255 documents (9.1 per cent) have a single author, and 29.09 per cent involve international co-authorship.

Table 1. Main information about the dataset (2,802 documents) as reported in Biblioshiny

Description	Results
Timespan	2014:2027
Sources (journals)	1,634
Documents	2,802
Articles / reviews	2,195 / 607
Annual growth rate %, 2014 to 2027 (Biblioshiny)	-22.17
Annual growth rate %, 2014 to 2026*	21.61
Average document age (years)	3.62
Average citations per document	26.33

Description	Results
Median citations per document*	7
Cited references in the export	0
Index keywords (ID)	13,841
Author keywords (DE)	8,697
Authors	12,328
Single-authored documents	255
Co-authors per document	4.99
International co-authorships %	29.09
Records lacking index keywords*	847 (30.2%)
Records lacking author keywords*	341 (12.2%)

** Computed by the authors from the Bibliometrix export file.*

Average citations (26.33) are raw Scopus counts and are not adjusted for time. The mean falls from 87.4 for papers published in 2014 to 1.1 for papers from 2026. Citations are highly skewed. The median is 7, 549 documents (19.6 per cent) have no citations, the top 1 per cent of documents (28 papers) hold 25.3 per cent of all citations, and the top 10 per cent hold 63.3 per cent. Index keywords are missing for 847 records (30.2 per cent) and author keywords for 341 (12.2 per cent), so the keyword maps rest on incomplete fields.

Annual Scientific Production

Table 2. Annual scientific production and mean citations per document, 2014 to 2027

Year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Documents	52	66	85	91	106	156	223	256	229	208	252	532	544	2
Mean citations	87.4	44.9	54.3	95.5	58.3	49.1	43.4	33.9	31.9	20.5	17.9	7.6	1.1	0.0

Output rises from 52 documents in 2014 to 544 in 2026. Over these thirteen years the compound annual growth rate is 21.6 per cent, calculated as (544/52)^(1/12) - 1. Growth was not smooth. Output rose every year to 256 in 2021, fell by 10.5 per cent in 2022 and by another 9.2 per cent in 2023, and recovered to 252 in 2024. The largest jump came in 2025, when output more than doubled to 532 (an increase of 111 per cent). The year 2026 is incomplete, since the file was built in September, yet it already exceeds 2025. Together, 2025 and 2026 account for 1,076 documents, or 38.4 per cent of the set.

A log-linear regression of yearly counts on year for 2014 to 2026 gives a slope of 0.1834 (standard error 0.0151, R^2 = 0.931). This implies annual growth of about 20.1 per cent, close to the compound rate. With thirteen points and a sharp step in 2025, the fit describes the series but should not be used to forecast it. The Biblioshiny figure of -22.17 per cent comes only from the two 2027 records at the end of the series and does not mean the field is shrinking.

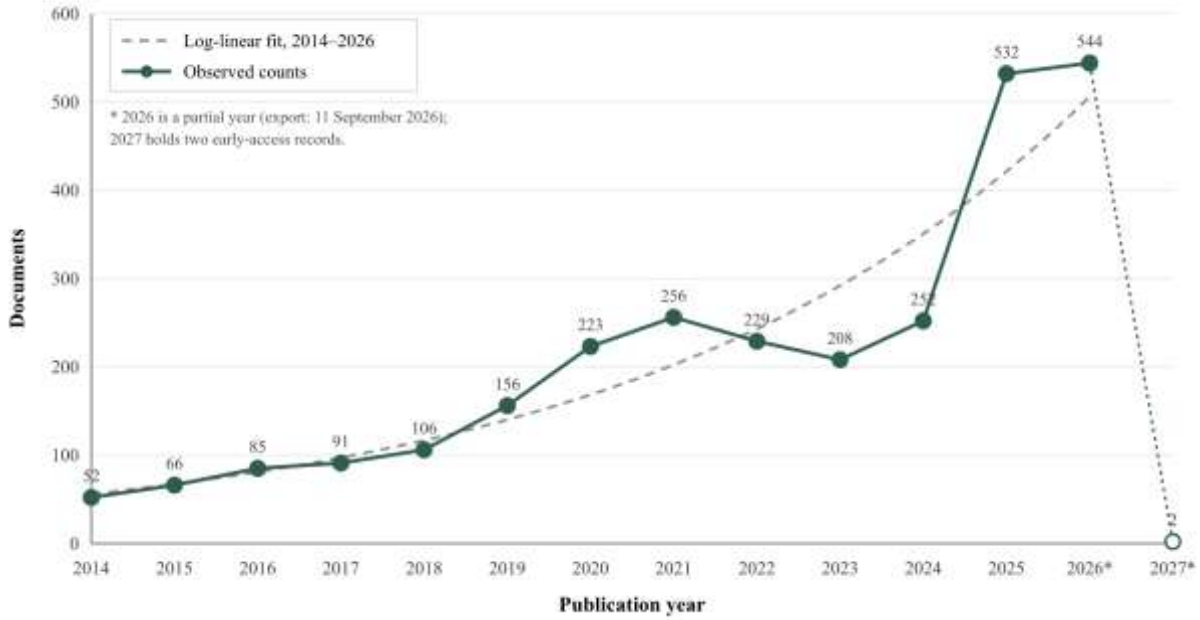


Figure 2. Annual scientific production, 2014 to 2027, with observed counts and fitted log-linear trend. 2026 is a partial year and 2027 holds two early-access records.

Most Cited Documents

Older papers still lead the citation counts. Of the ten most cited documents in Table 3, seven were published between 2014 and 2019.

Table 3. Ten most cited documents in the dataset

Rank	Document	Source	Citations
1	Jiang et al. (2017), Artificial intelligence in healthcare: Past, present and future	Stroke and Vascular Neurology	3,932
2	Egorova et al. (2017), Biological activity of ionic liquids and their application in pharmaceutics and medicine	Chemical Reviews	1,566
3	Wang et al. (2019), Review of smart meter data analytics	IEEE Transactions on Smart Grid	1,237
4	Bates et al. (2014), Big data in health care: Using analytics to identify and manage high-risk and high-cost patients	Health Affairs	1,022
5	Bibri (2018), The IoT for smart sustainable cities of the future	Sustainable Cities and Society	709
6	Ahmad et al. (2022), Data-driven probabilistic machine learning in sustainable smart energy systems	Renewable and Sustainable Energy Reviews	684
7	Ginsburg & Phillips (2018), Precision medicine: From science to value	Health Affairs	664
8	Hwang et al. (2020), Polymeric micelles for the delivery of poorly soluble drugs	Advanced Drug Delivery Reviews	660
9	Zhang & Letaief (2020), Mobile edge intelligence and computing for the Internet of Vehicles	Proceedings of the IEEE	531
10	Yetisen et al. (2018), Wearables in medicine	Advanced Materials	526

The list also shows how wide the search is. Only four of the ten (Jiang et al., 2017; Bates et al., 2014; Ginsburg & Phillips, 2018; Yetisen et al., 2018) deal directly with health care. The others cover ionic liquids, smart meters, sustainable cities, smart energy systems, drug-carrying micelles and vehicle networks. The second most cited paper (Egorova et al., 2017) mentions analytics only as one of many fields where ionic liquids are used, and Hwang et al. (2020) use "analytical" in the laboratory sense. Citation totals therefore describe the retrieved set, not a single research community.

Three-Field Plot

Figure 3 links authors, author countries and author keywords, following the threeFieldsPlot layout in Biblioshiny (Aria & Cuccurullo, 2017). Each field shows its 15 most frequent items. Each author is joined to the countries on their papers, and each country to the author keywords of papers from that country. The height of each box follows the total strength of its links, and the width of each band follows the number of shared documents. We used author keywords instead of merged keywords because the merged field is dominated by indexer labels such as "human", "humans" and "article", which say nothing about the topic. Author names are shown as exported (surname and initials) and were not disambiguated.

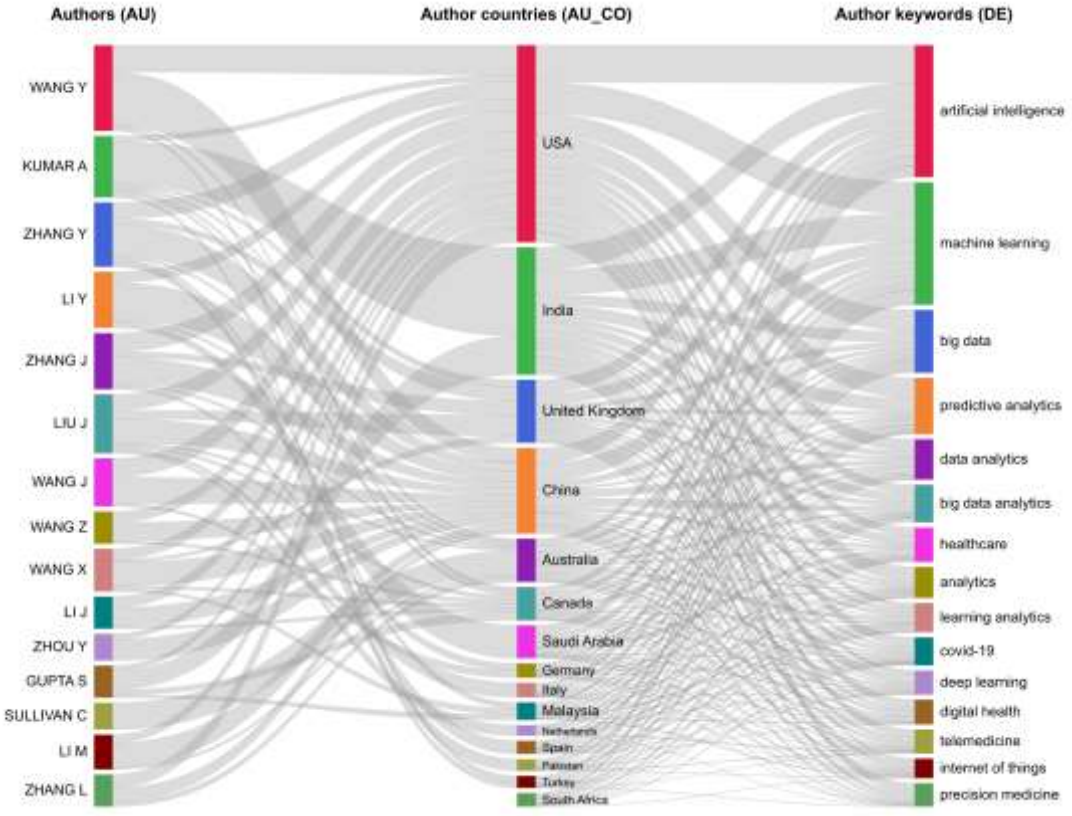


Figure 3. Three-field plot of authors (left), author countries (centre) and author keywords (right).

On the left, most of the top names are common Chinese or Indian surnames with one initial, such as Wang Y, Zhang Y and Kumar A. Each of these labels joins several different people (Table 4), and their links run mainly to China and India. The one clear individual is Sullivan C (Clair Sullivan), whose ten papers all carry Australian addresses. On the right, the United States sends the heaviest flows to "artificial intelligence" (89 shared documents) and "machine learning" (74), and India follows with 57 and 64. Health terms such as "digital health", "telemedicine", "precision medicine" and "covid-19" link most often to the United States, then to the United Kingdom and India. "Learning analytics" has a strong link to Australia (10 documents) given that country's smaller output.

Most Relevant Authors

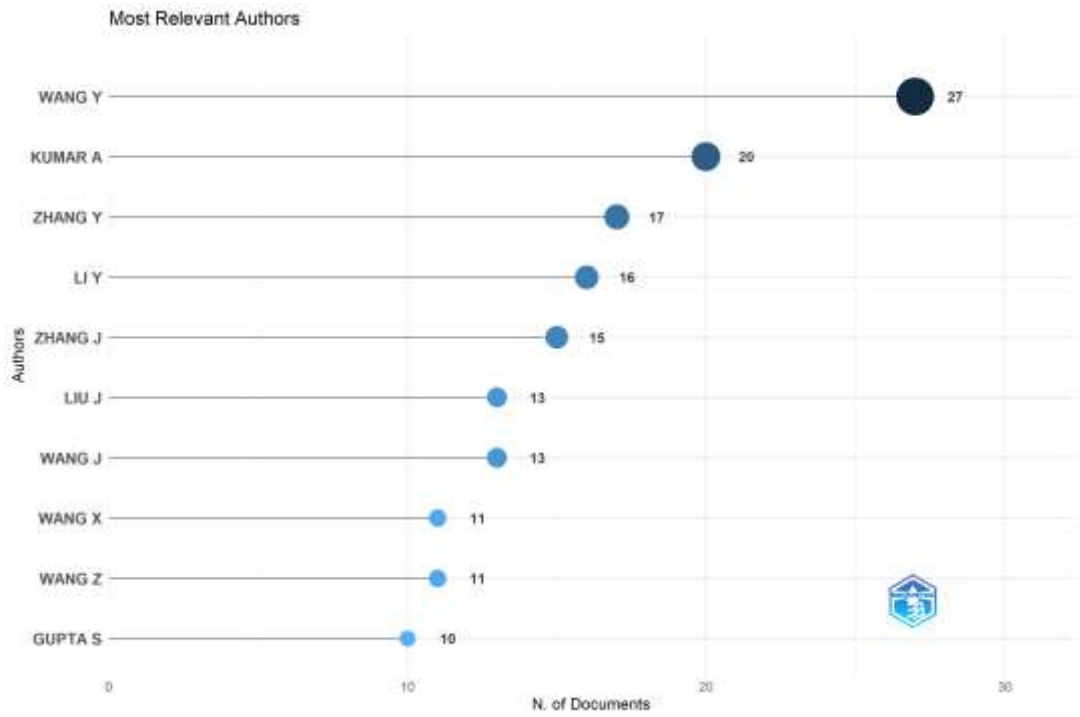


Figure 4. Most relevant authors by number of documents (Biblioshiny).

Table 4. Leading author labels and the number of distinct full names behind them

Author label	Documents (Biblioshiny)	Distinct full names in the export	Main countries
Wang Y	27	18	China
Kumar A	20	17	India
Zhang Y	17	15	China
Li Y	16	16	China
Zhang J	15	10	China
Liu J	13	12	China
Wang J	13	12	China
Wang X	11	9	China
Wang Z	11	11	China
Gupta S	10	7	India
Sullivan C	10	1	Australia

Wang Y appears 27 times across 25 documents because some papers list two authors with this label.

Figure 4 and Table 4 should be read together. Biblioshiny counts surname and initial, so the label Wang Y joins 18 different full names and Kumar A joins 17. No single researcher dominates the field. Clair Sullivan is the only author in the top group whose count belongs to one person, with ten papers, all from Australian institutions. This pattern fits the large and scattered author base of 12,328 names seen in Table 1.

Country Scientific Production

Biblioshiny's country production counts author appearances: 113 countries with frequencies that sum to 9,347. This is not a count of papers, because a paper with five American authors adds five to the United States. Table 5 therefore also reports how many documents carry at least one address in each country, taken from the affiliation field, and their mean citations.

Table 5. Leading countries, 2014 to 2027

Rank	Country	Author appearances	Share of 9,347	Documents with an address*	Mean citations per document*
1	United States	2,674	28.6%	897	32.3
2	India	1,063	11.4%	401	15.7
3	China	689	7.4%	273	43.7
4	United Kingdom	647	6.9%	280	34.4
5	Australia	558	6.0%	187	27.4
6	Canada	468	5.0%	176	24.5
7	Germany	240	2.6%	101	47.0
8	Saudi Arabia	197	2.1%	110	22.8
9	Italy	139	1.5%	70	29.7
10	Malaysia	123	1.3%	69	12.0

** Computed by the authors from the affiliation field of the Bibliometrix export.*

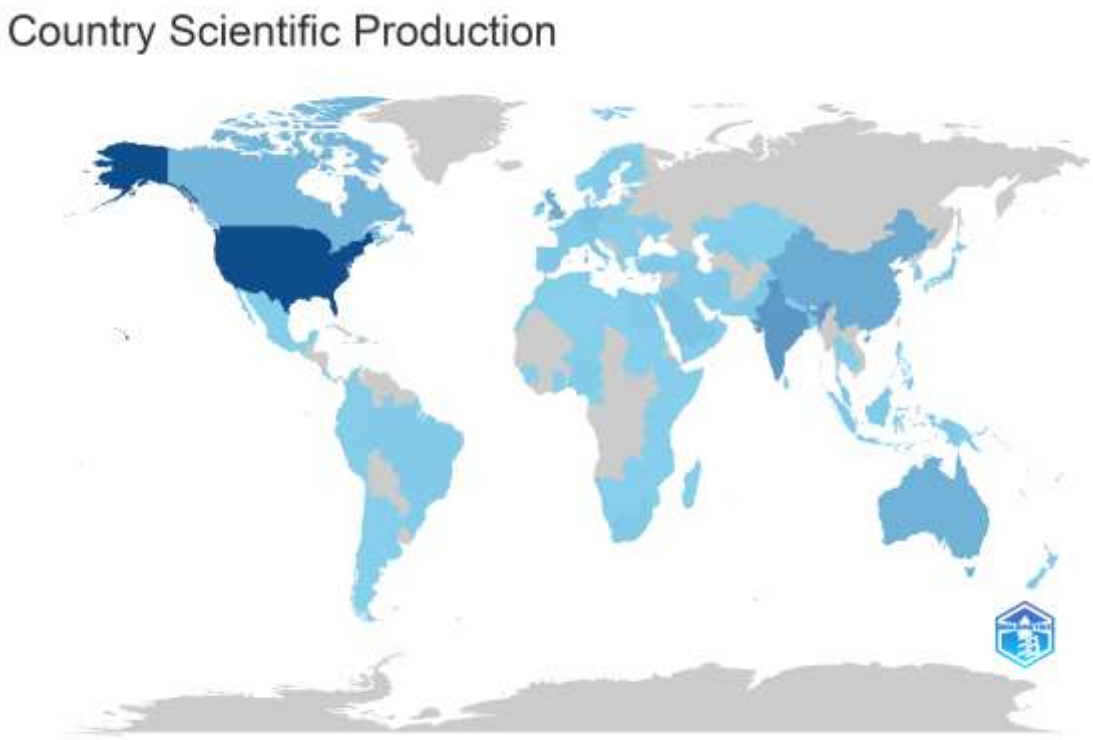


Figure 5. Country scientific production by author appearances, 2014 to 2027. Countries with no documents are shown in grey.

The United States leads on both measures, with 2,674 appearances (28.6 per cent) and 897 documents. India is second with 1,063 appearances, followed by China (689), the United Kingdom (647) and Australia (558). The top three countries hold 47.4 per cent of appearances, the top five 60.2 per cent and the top ten 72.7 per cent.

Citation impact does not follow output. Papers with an Indian address average 15.7 citations against 32.3 for papers with a US address, while German (47.0) and Chinese (43.7) papers have the highest averages in the top ten. These are raw counts and are not adjusted for year or document type.

A paper counts as multi-country when its addresses name more than one country. Of the 2,753 documents with usable addresses, 849 (30.8 per cent) are multi-country. They average 36.3 citations (median 9) against 22.3 (median 6) for single-country papers, and they hold 41.8 per cent of all citations. A Mann-Whitney test finds the difference significant

($z = 5.53$, $p = 3.3 \times 10^{-8}$). Reviews may explain part of the gap, since reviews average 44.5 citations against 21.3 for articles. The result shows an association, not a cause, and is in line with earlier work on international co-authorship (Glänzel & Schubert, 2001).

Fields of Application

Because "delivery" means different things, documents were grouped by words in their titles, abstracts and keywords. Table 6 shows the result. A document can fall into more than one field, and the word lists are simple, so the shares are rough guides rather than exact counts.

Table 6. Fields of application and analytics methods (word match on titles, abstracts and keywords)

Group	Documents	Share of 2,802	Documents in 2014	Documents in 2026
Health care (health, clinic, hospital, patient, medical)	1,698	60.6%	42	312
Education (education, student, teaching, e-learning, MOOC)	574	20.5%	9	123
Logistics, supply chain and e-commerce delivery	398	14.2%	4	105
Drug delivery and nanoparticles	257	9.2%	4	77
Energy and smart grids	158	5.6%	1	32
Public services and smart cities	80	2.9%	1	14
Software delivery and DevOps	50	1.8%	1	13
Method: artificial intelligence and machine learning	1,074	38.3%	3	304
Method: predictive analytics	612	21.8%	8	147
Method: big data	466	16.6%	13	46
Method: large language models and generative AI	63	2.2%	0	32

Groups overlap. Counts computed by the authors from the Bibliometrix export file.

Health care is the largest field by a wide margin, but its share is falling. Health terms appear in 81 per cent of the 2014 documents and in 57 per cent of those from 2026. Logistics moves the other way, from 4 documents (7.7 per cent) in 2014 to 105 (19.3 per cent) in 2026. Education grows steadily, from 9 documents in 2014 to 123 in 2026. Among methods, artificial intelligence and machine learning appear in 3 documents in 2014 and in 304 in 2026. Big data grew far more slowly, from 13 to 46 documents, and its share of yearly output fell from 25 per cent to 8 per cent. Large language models and generative AI appear for the first time in 2024 (4 documents) and reach 32 documents in 2026.

Keyword Co-occurrence

Three VOSviewer maps (van Eck & Waltman, 2010) were built on all keywords (author keywords plus index keywords) with minimum occurrence thresholds of 30, 35 and 40 and no thesaurus. A recount from the export gives 215, 169 and 138 terms at these thresholds, out of 19,547 distinct keywords. Each map shows four clusters. Circle size follows how often a keyword occurs, lines show co-occurrence, and colours mark the clusters assigned by the software. Clusters at one threshold are not the same objects as at another, and exact cluster sizes and software settings were not recorded.

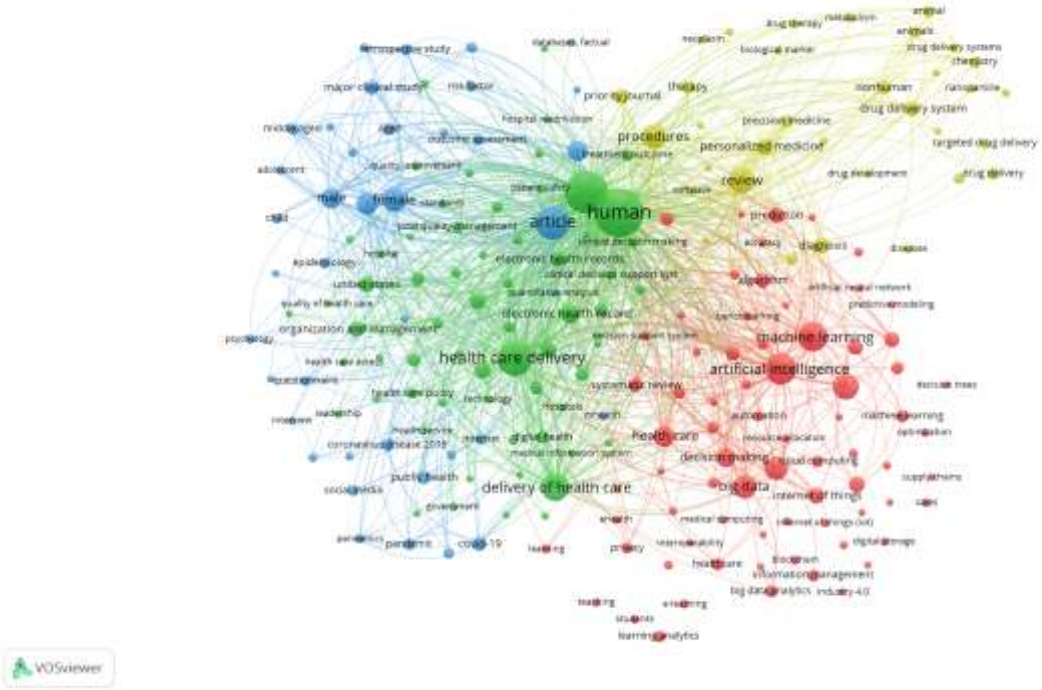


Figure 6. Keyword co-occurrence network, minimum 30 occurrences (215 terms, four clusters).

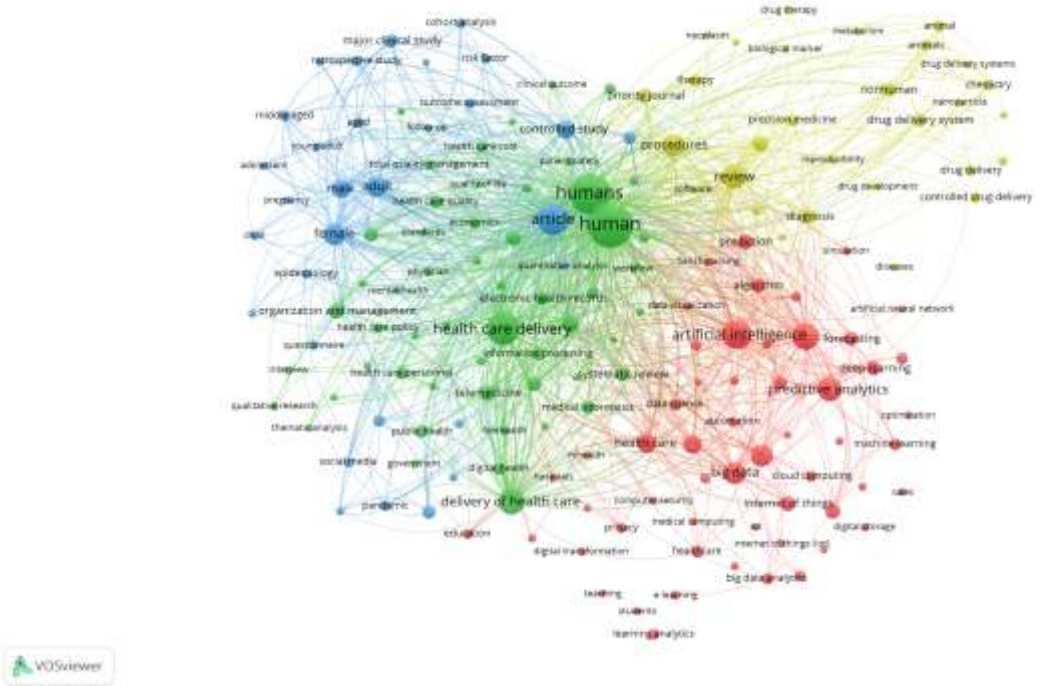


Figure 7. Keyword co-occurrence network, minimum 35 occurrences (169 terms, four clusters).

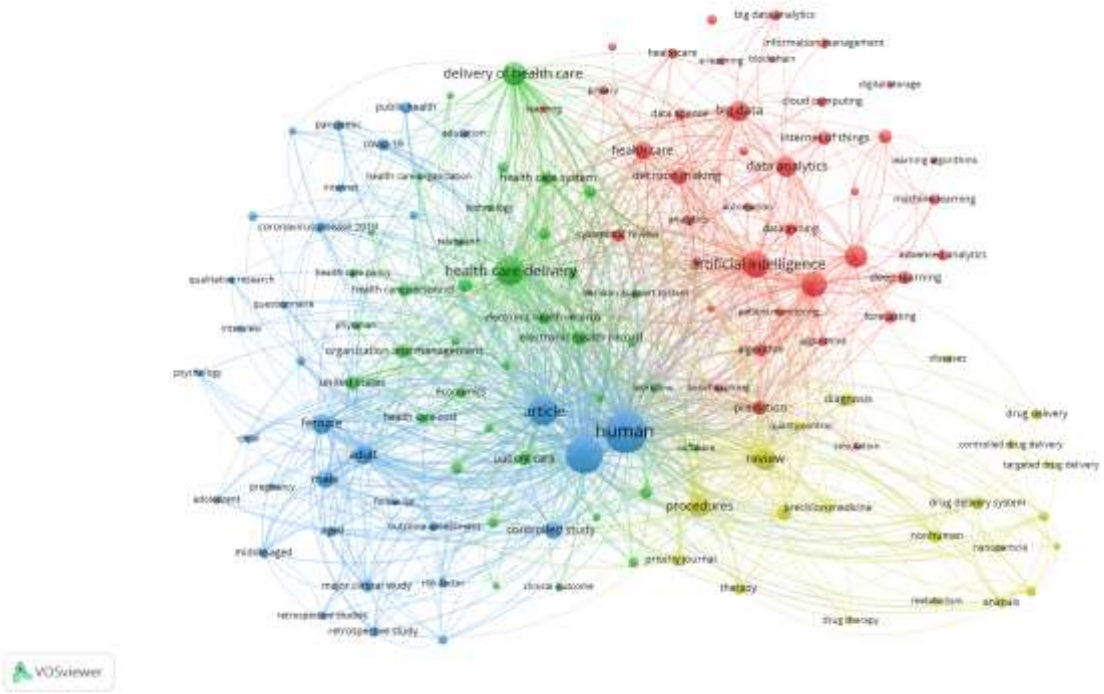


Figure 8. Keyword co-occurrence network, minimum 40 occurrences (138 terms, four clusters).

Table 7. Keyword clusters common to the three maps

Cluster (colour)	Main terms	Reading
Green	health care delivery; delivery of health care; electronic health record(s); organization and management; health care policy; telemedicine; digital health; total quality management; patient safety	Health-care delivery and management
Red	artificial intelligence; machine learning; big data; predictive analytics; data analytics; internet of things; cloud computing; deep learning; forecasting; decision making; blockchain; privacy; learning analytics	Analytics methods and digital technology
Blue	human; article; female; male; adult; aged; major clinical study; retrospective study; risk factor; epidemiology; covid-19; pandemic; public health	Clinical and population studies
Yellow	drug delivery system; drug delivery; nanoparticle; personalized medicine; precision medicine; diagnosis; therapy; procedures; nonhuman; animals	Drug delivery and precision medicine

At the threshold of 40, "human" moves from the green to the blue cluster.

The four clusters match the literature review. The green cluster is the health-system strand, the red cluster gathers the analytics methods, the blue cluster holds terms that describe clinical and population studies, and the yellow cluster is the drug delivery strand. "Human" (1,186 records), "humans" (917), "article" (600) and "review" (350) are among the largest nodes in every map. Indexers add these labels to describe document type and study subjects. They are not research topics, and they pull the network towards the medical records that carry them.

"Health care delivery" (603 records) and "delivery of health care" (414) are also mainly index terms. Of the 624 records tagged with either term, 71 have no health word in the title or author keywords, so part of the size of the green cluster comes from indexing rather than from what the authors say about their own work.

Logistics sits inside the red cluster rather than forming a group of its own. Terms such as "supply chains", "sales" and "industry 4.0" appear on the map at a threshold of 30 but are no longer shown at 40, which fits the smaller and newer

logistics strand in Table 6. Education terms such as "learning analytics", "e-learning", "students" and "teaching" form a small tail at the bottom of the red cluster at the thresholds of 30 and 35.

Mean publication years point the same way. Older terms include "forecasting" (2020.7), "total quality management" (2020.9), "big data" (2021.0) and "health care delivery" (2021.5). Newer terms include "machine learning" (2023.3), "deep learning" (2023.7), "artificial intelligence" (2024.1), "digital health" (2024.4) and "large language model" (2025.6). Rebuilding the maps on author keywords alone, with a thesaurus that merges variants such as "machine learning" and "machine-learning" and drops generic indexer labels, would give a cleaner picture of the topics.

Thematic Map

Figure 9 shows the Biblioshiny thematic map. Each bubble is a cluster of keywords. The horizontal axis (centrality) shows how strongly a theme links to other themes, and the vertical axis (density) shows how well developed it is internally. The labels "human" and "article" come from the index keyword field, so the map rests on that field.

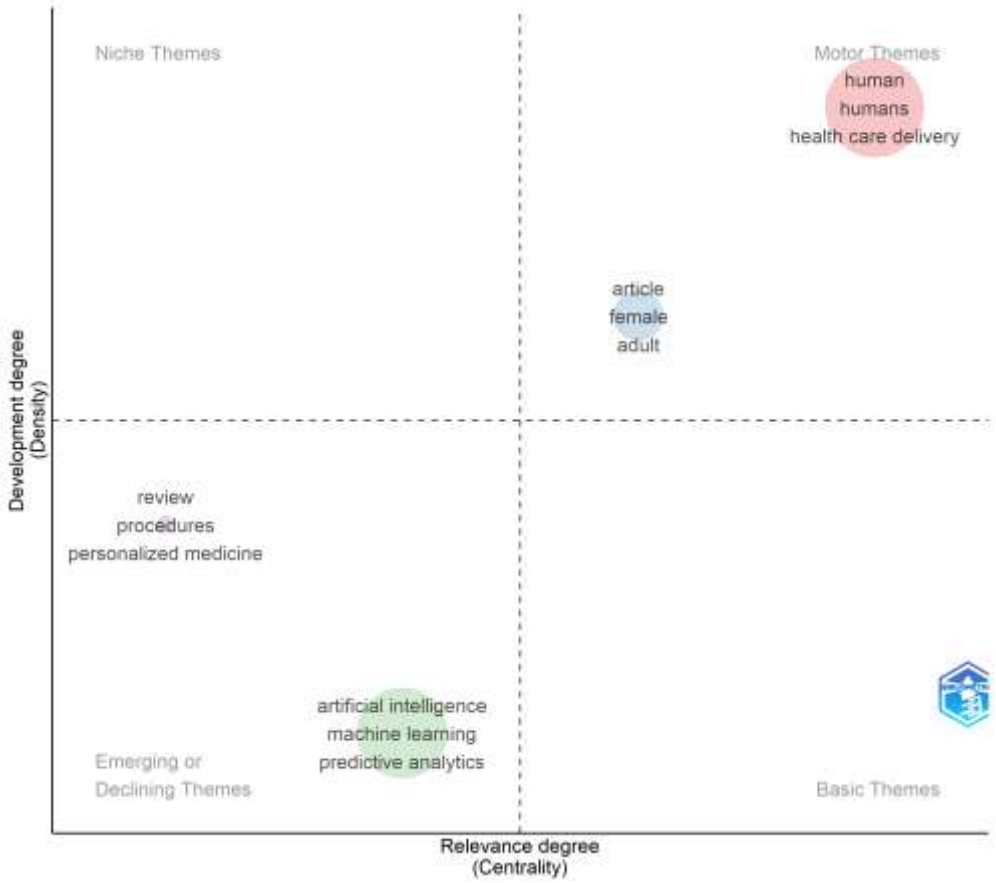


Figure 9. Thematic map of the dataset (Biblioshiny).

The theme led by "human", "humans" and "health care delivery" sits in the motor quadrant, with high centrality and high density, which fits the view of health-care delivery as the developed core of the field. A second theme, labelled "article", "female" and "adult", also lies in the upper right but closer to the centre; it collects terms from clinical studies. The theme of "artificial intelligence", "machine learning" and "predictive analytics" sits in the lower left quadrant (emerging or declining themes), near the centre lines. Given the strong growth of these terms since 2019 (Table 6), it reads as an emerging theme that is still loosely organised, not a declining one. A small theme of "review", "procedures" and "personalized medicine" also sits in the lower left.

5. FUTURE RESEARCH AGENDA

This review set out to trace how research on delivery and analytics has grown, who produces it and how its themes are organised. The 2,802 documents, read together with the literature, show a field that has grown fast but unevenly. Output rose by about 21.6 per cent a year between 2014 and 2026, more than doubled in 2025, and is concentrated in health care and in a few countries. Several gaps remain. Some lie in the field itself and some in the way the database captures it. The agenda below has six areas, starting with method and ending with substance.

1. Strengthening the bibliometric foundation

Because the cited-reference field in the export is empty, co-citation analysis and bibliographic coupling (Small, 1973; Kessler, 1963) could not be run, and the thematic structure had to be read from keywords. Future studies should export cited references, so that co-citation can show the foundational works and coupling can show the current research front (Donthu et al., 2021; Zupic & Čater, 2015). The search string "Delivery AND Analytics" also groups unrelated fields. Separate queries for health-care delivery, drug delivery, logistics and education, limited to titles, abstracts and author keywords, would give a cleaner map of each.

2. Logistics and last-mile delivery

Logistics is the fastest growing field in Table 6 but is still small. Existing studies show that combining machine learning predictions with order assignment and scheduling saves cost (Liu et al., 2021; Kandula et al., 2021), and that drones, robots and lockers change how the last mile is organised (Demir et al., 2022; Lyu & Teo, 2022; Shuaibu et al., 2025). Many of these studies test their models on data from one firm or one city. Future research could compare methods on shared data sets, add emissions and working conditions to the objectives, and test whether models built in one market hold in others.

3. From prediction to action in health care

Health care has many predictive models but fewer studies of what happens after they are put to use. Early work already called for fitting analytics into clinical workflow (Fihn et al., 2014) and for governance at each stage of a model's life (Cohen et al., 2014). Reviews of artificial intelligence in imaging and of conversational agents mostly assess accuracy, efficiency and usability (Khalifa & Albadawy, 2024; Milne-Ives et al., 2020). Studies that follow tools in routine care and measure cost, patient outcomes and staff workload would show whether the expected gains reach patients.

4. Large language models and generative AI

Large language models and generative AI appear in the data set only from 2024, with 63 documents by September 2026. Early work maps their use in health care (Gencer & Gencer, 2025) and in cardiovascular population health (Meder et al., 2025). Research is needed on where these models help delivery decisions such as triage, documentation, customer service and route planning, how their errors can be caught, and how they compare with simpler predictive models on the same tasks.

5. Equity, privacy and trust

Several papers show that analytics can widen gaps between groups (Yao et al., 2022; Thomasian et al., 2021) and that privacy concerns limit data sharing between institutions (Froelicher et al., 2021; Löfgren & Webster, 2020). Future work could test privacy-preserving methods such as federated analytics outside medicine, for example in logistics and public services, and measure who gains and who loses when a delivery service starts to rely on predictions.

6. Collaboration and geographic diversity

The United States, India, China, the United Kingdom and Australia hold 60.2 per cent of author appearances. India is the second largest producer, but its papers average about half the citations of US papers. Multi-country papers draw more citations on average, a pattern also reported in other fields (Glänzel & Schubert, 2001). Partnerships between high-output and high-impact countries, and more studies from Africa, South America and Southeast Asia, which are thinly represented on the country map, would widen the evidence base.

6. CONCLUSION AND LIMITATIONS

The analysis covers 2,802 documents retrieved from Scopus with the query "Delivery AND Analytics" and published between 2014 and 2027. For RQ1, output rose from 52 documents in 2014 to 544 in 2026, an average growth of 21.6 per cent a year. The path was uneven: output dipped in 2022 and 2023, then more than doubled in 2025. The years 2025 and 2026 hold 38.4 per cent of the set, and 2026 is incomplete. Mean citations fall from 87.4 per paper for 2014 to 1.1 for 2026, because recent papers have had less time to be cited. The median is 7 citations, 549 papers have none, and the top 10 per cent of papers hold 63.3 per cent of all citations, so impact is concentrated in a small set of mostly older work.

For RQ2, the field is large and spread out, with 12,328 authors and 1,634 sources. Papers have 4.99 authors on average and only 9.1 per cent are single-authored. The United States accounts for 28.6 per cent of author appearances, India for

11.4 per cent and China for 7.4 per cent. The most productive author labels (Wang Y, Kumar A, Zhang Y) each combine many different people, so author rankings should be read with care. Multi-country papers (30.8 per cent) average 36.3 citations against 22.3 for single-country papers. The gap is statistically significant, though reviews account for part of it.

For RQ3, the keyword maps at thresholds of 30, 35 and 40 give the same four clusters: health-care delivery and management, analytics methods and digital technology, clinical and population study terms, and drug delivery with precision medicine. Health care is the core of the field and appears in about six of every ten documents, but its share is falling as logistics and education studies grow. Methods have moved from big data towards machine learning, artificial intelligence and, since 2024, large language models (Bates et al., 2014; Jiang et al., 2017; Liu et al., 2021; Gencer & Gencer, 2025).

For RQ4, the main limits come from the export and the search. All cited-reference fields are empty, so co-citation analysis and bibliographic coupling cannot be done. Index keywords are missing for 30.2 per cent of records, and generic indexer labels such as "human" and "article" dominate the maps. The query joins fields that share a word but little else, such as nanoparticle drug carriers and parcel routing, so citation totals and clusters describe the retrieved set rather than one research community. The two 2027 records were kept to match the screening flow, which makes Biblioshiny report a negative growth rate. Recent papers have had less time to gather citations, so their lower counts do not by themselves show lower quality.

Within these limits, the counts and maps show how research on delivery and analytics has grown, where it comes from and how its themes have shifted. Later studies would gain from narrower queries for each field of delivery, an export that includes cited references, and conclusions that stay within what the chosen data can support.

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