

OVERVIEW



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On the application of machine learning in astronomy and astrophysics: A text-mining-based scientometric analysis

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Abstract

Since the beginning of the 21st century, the fields of astronomy and astrophysics have experienced significant growth at observational and computational levels, leading to the acquisition of increasingly huge volumes of data. In order to process this vast quantity of information, artificial intelligence (AI) techniques are being combined with data mining to detect patterns with the aim of modeling, classifying or predicting the behavior of certain astronomical phenomena or objects. Parallel to the exponential development of the aforementioned techniques, the scientific output related to the application of AI and machine learning (ML) in astronomy and astrophysics has also experienced considerable growth in recent years. Therefore, the increasingly abundant articles make it difficult to monitor this field in terms of which research topics are the most prolific or novel, or which countries or authors are leading them. In this article, a text-mining-based scientometric analysis of scientific documents published over the last three decades on the application of AI and ML in the fields of astronomy and astrophysics is presented. The VOSviewer software and data from the Web of Science (WoS) are used to elucidate the evolution of publications in this research field, their distribution by country (including co-authorship), the most relevant topics addressed, and the most cited elements and most significant co-citations according to publication source and authorship. The obtained results demonstrate how application of AI/ML to the fields of astronomy/astrophysics represents an established and rapidly growing field of research that is crucial to obtaining scientific understanding of the universe.

This article is categorized under:

Algorithmic Development > Text Mining

Technologies > Machine Learning

Application Areas > Science and Technology

KEYWORDS

astronomy, astrophysics, machine learning, scientometrics, text mining

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1 | INTRODUCTION

Astronomy and astrophysics rely on the acquisition, storage, and analysis of large datasets. Regardless of whether these are obtained through telescopes, particle detectors, or numerical simulations, they are processed in a way that allows scientific knowledge about the universe to be acquired. Thanks to advances in optical and computer technology, there has been a dramatic growth in the observational and computational aspects of astronomy and astrophysics over the last two decades. This has resulted in extraordinarily large datasets (currently approaching the exabyte scale) that are necessitating new methods of analysis to facilitate scientific discovery (Fayyad et al., 1996), giving rise to the era of so-called Big Data (Brunner et al., 2002; Feigelson & Babu, 2012; Khalil et al., 2019; Zhang & Zhao, 2015). One of these methods is the use of artificial intelligence (AI), which, together with data mining, allows researchers to discern patterns in the data and thus model, classify or predict the behavior of astronomical phenomena and objects (Ball & Brunner, 2010; Borne, 2009; Graham et al., 2013; Ivezić et al., 2014; Wang et al., 2018).

Within AI, the branch of machine learning (ML) has been of extraordinary interest in the astronomical/astrophysical field. ML is the process in which a machine (computer) autonomously learns to identify patterns to make classifications or predictions without having been expressly programmed to do so. Various ML techniques can be applied to astronomy and astrophysics, producing extremely diverse results, including principal component analysis (PCA) for the classification of the spectra of stars (Singh et al., 1998; Xiang et al., 2017), exoplanets (Damiano et al., 2019), galaxies (Conselice, 2006; Kochi et al., 2017), and quasars (Davies et al., 2018; Yip et al., 2004); random forests (RF) for the estimation of photometric redshifts (Carrasco Kind & Brunner, 2013; Mucesh et al., 2021) and the classification of asteroids (Chao et al., 2017); decision trees (DT) for the classification of stellar (Hinnens et al., 2017) and galaxy morphologies (Reza, 2021); support vector machines (SVM) for the prediction of solar flares (Qahwaji & Colak, 2007), the detection of gravitational waves (Biswas et al., 2013) and the classification of astronomical objects (Sunitha et al., 2020); artificial neural networks (ANN), which constitute the basis of the ML subfield called deep learning (DL, i.e., structured or hierarchical automatic algorithms that emulate human learning), for the detection of gamma ray bursts (Ball et al., 2004; Singh et al., 2022), the analysis of asteroid composition (de León et al., 2010), pulsar identification (Eatough et al., 2010) and the detection of gravitational lenses (Agnello et al., 2015); and, finally, convolutional/deep neural networks (CNN/DNN), which were developed from ANN, for the classification of transit objects (Gómez et al., 2020) and galaxies (Dieleman et al., 2015), photometric redshifts estimation (Hoyle, 2016), and the identification of the astronomical sources of radio waves (Lukic et al., 2020).

In line with these increasingly powerful techniques, there has been a plethora of scientific output on the topic of AI and ML as applied in astronomy and astrophysics. This growing pool of scientific publications introduces difficulties in the identification of the most novel contributions or prolific research topics or which authors or countries are at the forefront of this research field. A solution to this issue may be offered by scientometrics, a discipline that uses different techniques and tools to study the scientific output on a topic by measuring and analyzing it. A scientometric study can provide a macroscopic view of an extensive set of scientific publications, with methods such as text mining allowing the production of relational maps related to the scientific development of a given line of research. This makes it possible to identify patterns in terms of the most productive scientific journals, the countries with the highest research output or the most prolific authors, and the topics on which recent research has been focusing.

In this respect, despite the recent publication of several very comprehensive review articles on the use of AI/ML techniques in the field of astronomy/astrophysics (Fluke & Jacobs, 2020; Kremer et al., 2017; Longo et al., 2019; Wang et al., 2018), to the best of the authors' knowledge, there is no updated analysis that uses scientometrics to address this issue.

Consequently, this work comprises a text-mining-based scientometric study of the scientific output in the last three decades regarding the application of AI and ML to the fields of astronomy and astrophysics.

2 | MATERIALS AND METHODS

2.1 | Scientometrics and text-mining

Scientometrics concerns the quantitative aspects of scientific information in relation to its production, dissemination and utilization to thoroughly understand the mechanisms and evolutionary drivers underlying scientific research (Chellappandi & Vijayakumar, 2018). As a research technique, it is located in the information and library sciences and

employs quantitative methods, for example, text mining, to explore bibliographic data, such as author, publication year, and country of origin (Broadus, 1987). A scientometric analysis can be wielded to produce a representative outline that describes a collection of scientific documents. Prior studies have used scientometrics tools to explore myriad aspects of the scientific literature, from keywords and topics (Thongpapanl, 2012) to authors, institutions, and countries. This information can be evaluated using a wide set of indicators, such as the number of citations or the volume of published articles (Song & Ding, 2014). The current study draws on some of these indicators to present a holistic perspective of the technique, enabling readers to gain an insight into the possible outcomes thanks to its unique advantages as well as the implementation needs.

As yet, there is no consensus on how to best measure the virtues of scientific literature. In general, productivity and influence are the two common ways with which to measure research output (Podsakoff et al., 2008); the former is usually based on the total number of publications, while the latter is captured by the number of citations. However, several other useful scientometric indicators have also been established, often with remarkable results.

2.2 | Software

In the current study, the Java-based VOSviewer software (version 1.6.17), developed at Leiden University, the Netherlands, is utilized to perform the scientometric mapping and text mining (Van Eck & Waltman, 2014). VOSviewer first mines texts to identify the keywords used in a set of research articles, and then generates bibliometric maps, referred to as landscapes, via the visualization of similarities (VOS) mapping technique (Van Eck & Waltman, 2010). By depicting these landscapes in different ways, inferences can be made on the publications' characteristics.

Briefly, using bibliographic data to create graphical maps, VOSviewer can provide a representation of serviceable characteristics, including bibliographic coupling (Kessler, 1963), co-citation (Small, 1973), and co-authorship and the co-occurrence of author keywords.

VOSviewer implements the so-called Leiden algorithm. Notably, the use of the Leiden algorithm to find well-connected clusters in a network means that this technique addresses some of the deficiencies inherent in the Louvain algorithm. In this sense, the Louvain method allows researchers to identify communities within networks. For each community, the algorithm maximizes a modularity score that quantifies how well nodes are assigned to the communities. In other words, it compares the densities of the connections between a community's nodes with those for the same nodes in a random network. As a hierarchical clustering algorithm, the Louvain algorithm brings identified communities into a single node through recursive merging, performing modularity clustering on the condensed graphs (Blondel et al., 2008). Specifically, the Louvain method can identify clusters that have arbitrary connections. Nonetheless, the communities detected by the Leiden algorithm have guaranteed connections. Moreover, the iterative use of the Leiden algorithm enables convergence on a partition wherein all population subsets are optimally locally assigned (Traag et al., 2019).

The abovementioned VOS algorithm used by the VOSviewer for the graph layout was developed by authors Van Eck and Waltman (2007). The low-dimensional visualization provided by VOS provides the highest possible degree of accuracy as objects are located so that the distance between any given object pair well represents their similarity. VOS grounds upon the notion of minimizing the weighted sums of all object pairs' squared Euclidean distances. During the summation, the greater a pair's similarity, the greater their squared distance weight.

2.3 | Indicators

We focused on the indicators outlined in the following to summarize the provenance of the application of AI/ML to the astronomy and astrophysics research fields.

2.3.1 | Production and chronology

The first analyzed characteristic is the quantity of scientific material produced regarding the investigated topic, that is, the application of AI/ML to astronomy and astrophysics. This reveals the most productive countries in this field, which can subsequently be compared at the level of the gross domestic product (GDP). Furthermore, by clarifying how this stream of research has occurred chronologically, we can then estimate whether this can be considered a *hot topic*.

2.3.2 | Topics analysis

Topic mapping analysis unveils the main (occasionally unseen) topics that are mooted by the bibliographic materials in the investigated research field. Hence, through the application of a factual methodology, this analysis allows so-called idle topics (i.e., subtle or obscure) lying within the vast quantity of bibliographic material to be transformed into clear-cut visual illustrations of the subject clusters and their correlations. This tool has already shown great potential in the fields of text mining and scientometrics (Yan et al., 2012). It relies on dissimilarities between probability distributions, that is, how both an individual semantic element and all semantic elements are, respectively, distributed across the group of all topics (Van Eck et al., 2010). If these distributions are highly disparate, this indicates that the semantic element probably links to a specific concept, whereas equivalent distributions suggest that the semantic element is not coupled in this way. The relationships between the keywords are computed according to how often they appear in the articles; in other words, the co-occurrence of two terms in numerous articles proposes that these have a robust relationship. The results of such an analysis allow the grouping of the terms into clusters on a map (Van Eck & Waltman, 2007) via the abovementioned VOS technique.

2.3.3 | Citations and highly cited elements

Examining which articles, authors and journals have the most citations can reveal the key research elements in the application of AI/ML to astronomy and astrophysics.

2.3.4 | Co-citation analysis

In a co-citation analysis, weights are applied corresponding to the co-citation strength, referring to the tendency for certain journals or authors to be co-cited in one article. This bases on the understanding that articles authored by frequently co-referenced researchers tend to deal with corresponding ideas (Boyack & Klavans, 2010). Utilizing the clustering technique of Van Eck (Waltman & Van Eck, 2012), VOSviewer generates a co-citation matrix that depicts the clusters of closely related articles. At least 20 citations are required for a co-citation analysis in order to ensure that the data visualization contains minimal disorder. This work also employed lower thresholds (5, 10, and 15 citations) to identify the optimum level. Co-citation analysis can be conducted at the author level, wherein the co-citation value is calculated according to the correlations between a given author's articles, or the journal level, using the relationships among journals. The co-citation structures unveiled through this technique offer an in-depth insight into the application of AI/ML to the fields of astronomy and astrophysics.

2.3.5 | Overlay visualization

Overlay visualization allows other information types, for example, publication year, to be superimposed onto topic analysis or citation analysis, thereby depicting the trend of a research stream or set of collaborative works. This technique can automatically identify trends, making it one of the most important scientometric tools (Leydesdorff & Bornmann, 2012) as it can unequivocally portray the chronological development of a topic. VOSviewer can hereby produce a map illustrating the associations between specific elements, onto which additional datapoints containing further information (e.g., publication age and citation impact) can be superimposed.

2.4 | Data acquisition

2.4.1 | Source of data

The most extensive bibliographic sources for research data are generally considered to be the Web of Science (WoS) and Scopus databases (Zhu & Liu, 2020). The former, which is both multidisciplinary and selective, comprises numerous specialized indexes. Its main component is its Core Collection (WoS CC), constituting six main citation indexes,

namely the Science Citation Index Expanded (SCIE), the Arts and Humanities Citation Index (AandHCI), the Social Science Citation Index (SSCI), the Conference Proceedings' Citation Index (CPCI), the Book Citation Index (BKCI), and recently, the Emerging Sources Citation Index (ESCI) (Ahmad & Batcha, 2019). While Scopus is also multidisciplinary (Baas et al., 2020), it additionally integrates content from several more specialized databases, including Embase, Fluidex, Compendex, World Textile Index, Medline, Geobase, and Biobase and Medline (Valderrama-Zurián et al., 2015). Nonetheless, as the first large-scale international source of bibliographic data, WoS has become the most influential and has been the primary database employed in scientometrics (Li et al., 2018).

Google Scholar (GS) is another potential source of bibliographic information (Halevi et al., 2017), and the free availability of its content on a non-subscription basis is one of its main advantages. Its other advantage is its much broader and deeper scope, even though it lacks clearly defined boundaries. While its advantages give GS an edge over WoS and Scopus, they also diminish its reliability as a bibliographic database. GS is also in particular plagued by reduced stability, transparency, and precision (Orduña Malea et al., 2017). Many other useful data sources exist, including the relatively new and access-free ResearchGate, Microsoft Academic, CrossRef, and OpenCitations (Visser et al., 2021); however, they still have questionable validity.

Based on the reasoning above, the WoS database is used in this study identifying research applying AI/ML to the fields of astronomy and astrophysics.

2.4.2 | Collected data

The extraction of data from WoS was performed on November 1, 2021. The search period was 1989 until the data collection date. This way, by considering all publications given by the search, 2723 relevant articles were found.

For each identified publication, numerous data fields were extracted, such as title, author(s), country of origin, keywords, abstract, journal, and publication date. The search criteria, that is, the key terms used in the search, are presented in Table 1, together with the number of intermediate results of each term (in decreasing order of relevance).

As the table shows, the searches linked concepts from the field of AI/ML with the fields of astronomy or astrophysics to identify relevant records. We hereby availed of most general AI/ML concepts as proposed by a recent study (Shnurenko et al., 2020).

Beyond the general application areas, keywords referring to specific applications and algorithms (Bonaccorso, 2018) were also incorporated; however, these occasionally returned insignificant results when considered in isolation. Keywords that returned innumerable scientific articles (e.g., “dataset” or “clustering”) were excluded as these terms did not inevitably signify the relevance of the article to the topic of interest. Some of the more atypical or highly distinct terms

TABLE 1 Search criteria

Keywords	Number of intermediate results
(Astronomy OR Astrophysics) AND	
(Machine Learning OR	775
Neural Networks OR	524
Big Data OR	397
Deep Learning OR	238
Artificial Intelligence OR	190
Genetic Algorithm OR	142
Random Forest OR	129
Cloud Computing OR	119
Support Vector Machines OR	84
Feature Selection OR	47
Decision Trees OR	36
K Nearest Neighbors OR	21
Gradient Boosting OR	12
Naïve Bayes)	9

gave negligible results when used alone; it should further be noted that these results had already been returned in the previous general searches using key terms such as “artificial intelligence,” “machine learning,” and “big data.”

The data produced by the search were first exported into text format; following this, outliers and incomplete records were removed and the records were prepared for import into VOSviewer.

3 | RESULTS AND DISCUSSION

3.1 | Output and chronological analysis

Figure 1 represents the chronological evolution of the number of publications related to the application of AI/ML in astronomy/astrophysics.

As mentioned in Section 1, AI and ML techniques have experienced exponential development in the last few decades, as can be seen in Figure 2, where the total publications regarding the search criteria of Table 1, without the terms “Astronomy” and “Astrophysics,” have been depicted.

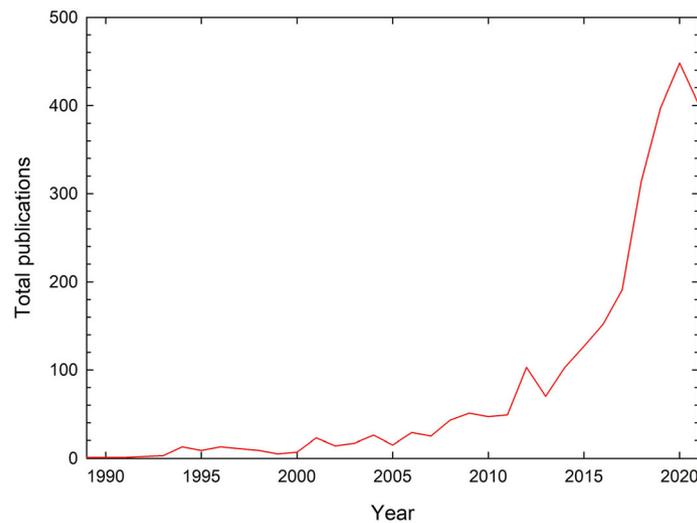


FIGURE 1 Timeline of the number of publications considering the search criteria of Table 1.

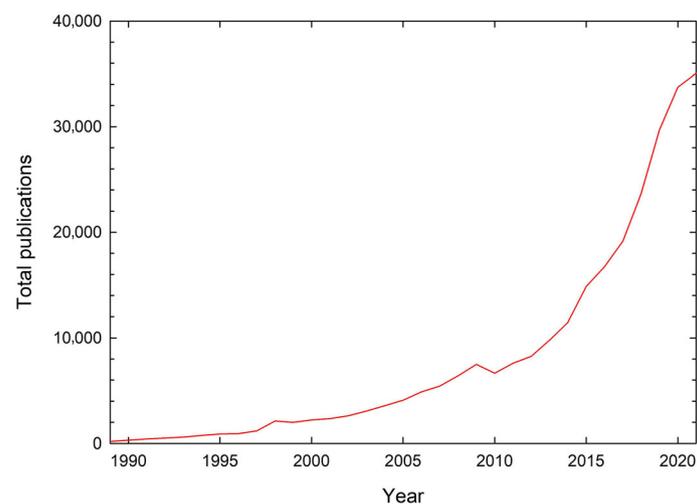


FIGURE 2 Timeline of the number of publications considering the search criteria of Table 1 but without the terms “astronomy” and “astrophysics.”

TABLE 2 Top 15 most productive WoS categories

Category	No. of publications
Astronomy Astrophysics	1761
Computer Science Information Systems	253
Optics	236
Engineering Electrical Electronic	232
Computer Science Theory Methods	224
Computer Science Artificial Intelligence	220
Computer Science Interdisciplinary Applications	211
Physics Particles Fields	116
Physics Multidisciplinary	85
Physics Applied	84
Computer Science Software Engineering	65
Computer Science Hardware Architecture	64
Instruments Instrumentation	58
Physics Nuclear	54
Imaging Science Photographic Technology	49

Consequently, as shown in Figure 1, the scientific output related to the application of these techniques in astronomy or astrophysics has also seen dramatic growth (almost proportional), especially after 2005. Specifically, 488 of the 2723 articles found in WoS during the data acquisition stage had been published during 2020; meanwhile, for the year 2021, 401 had been published by the data collection date (November 1, 2021). Furthermore, 1751 articles have been published in just the last 5 years. Meanwhile, 1648 of the 2723 articles were published in open-access journals according to the results from WoS. Unlike the conventional subscription-based model, which requires readers to pay to access scholarly publications, open-access publishing enables research results to be disseminated to a wide audience at no cost to the readers. In this sense, the fact that most of the publications are open access (60%) may indicate that there is a certain trend toward the democratization of knowledge, at least as far as the field of AI/ML applied to astronomy/astrophysics is concerned.

Another interesting analysis that can be performed in relation to the total number of articles published in this line of research is their distribution among the different WoS categories or disciplines. Table 2 lists the 15 categories with the most publications.

As can be seen (and as might be expected), the Astronomy Astrophysics category clearly leads this list, with 1761 publications. However, the table also contains several well-represented fields related to computer science, engineering, and optics. The less productive categories include those related to physics (specific and general) and instrumentation.

The global scientific output in this field according to the number of articles published by each country is depicted as a map in Figure 3.

As Figure 3 clearly shows, scientific research articles related to this topic are prevalently produced in the United States (948), China (483), and the United Kingdom (478), followed by Germany (369). A substantial amount of scientific research on the application of AI/ML to the astronomy and astrophysics fields has also been produced in several other European countries.

Notably, the two countries generating the most research articles on this topic are simultaneously the two largest global economies in terms of GDP, namely the US (\$20.94 trillion) and China (\$14.72 trillion) (WorldBank, 2021a). To delve deeper into this analysis, Figure 4 classifies the top 15 most productive countries in relation to their incomes.

It emerges that the majority of the 15 countries producing the most publications are high-income nations, as per the World Bank classification (WorldBank, 2021b). The exceptions are the upper-middle-income nations China and Brazil and the lower-middle-income nation India. According to the World Bank classification, the most productive low-income country, regarding the number of publications, is Ethiopia; having published two articles, it achieves a rank of 65.

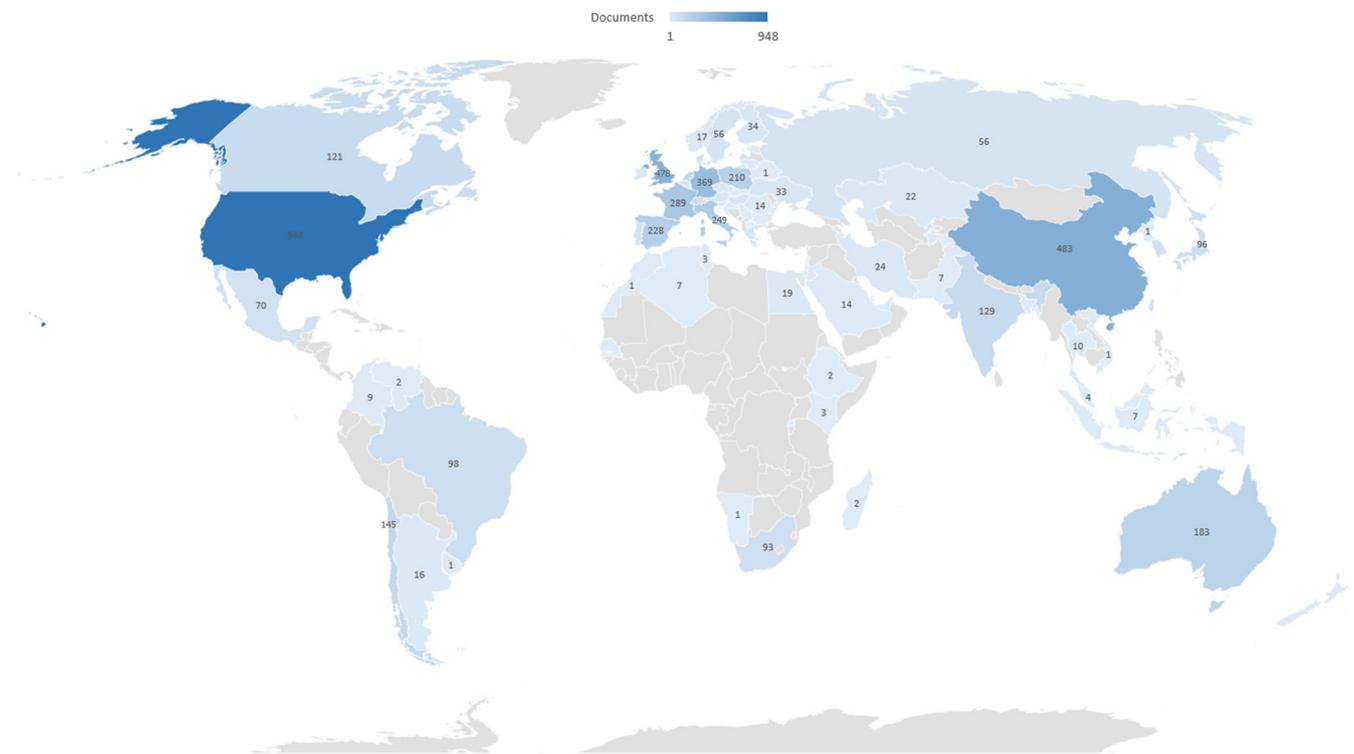


FIGURE 3 Number of publications by country.

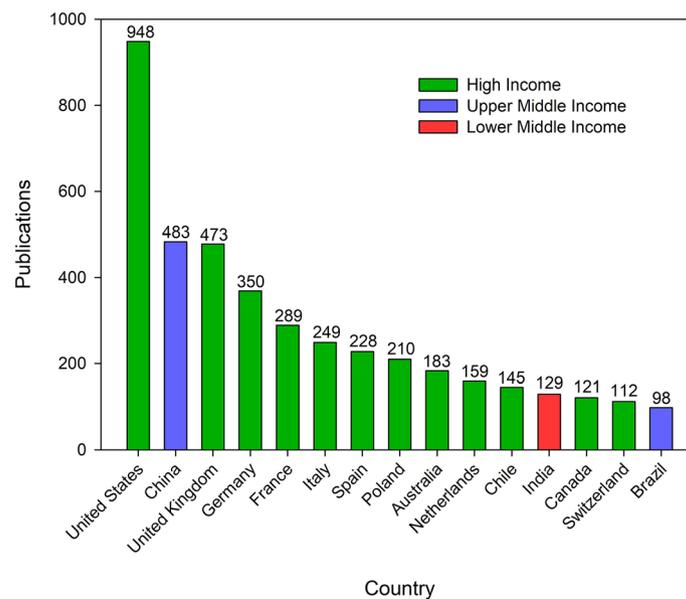


FIGURE 4 Top 15 most productive countries classified according to their incomes.

To compare the data in Figure 4 with the pattern of global scientific production (taking into account all disciplines and subjects), Figure 5 portrays the 15 most productive countries—in terms of published articles—in all scientific fields for the 1996–2020 period (*Source*: Scimago).

In both figures, the first four positions are occupied by the same countries and in the same order. However, while Japan is in fifth place for the scientific production for all categories, it is not among the first 15 for AI/ML in astronomy/astrophysics publications. Russia and South Korea are similarly absent from Figure 4. On the other hand, European countries such as France, Italy, Spain, and the Netherlands appear in both figures, and in the same order. It

is worth highlighting that in Figure 5, India occupies a more advanced place than it does in Figure 4, especially given its World Bank classification as a low-income country. Finally, it should be noted that while Chile is not among the 15 countries with the most scientific output, it does appear among the 15 most prolific in the field of AI/ML applied to astronomy/astrophysics. This fact could be explained by the historical astronomical tradition that it enjoys for hosting one of the best places on Earth to observe the sky—the Atacama Desert.

Following the examination of the evolution of scientific output, including its distribution by country, the following presents an analysis of collaborations in the publishing of work related to the application of AI/ML to astronomy/

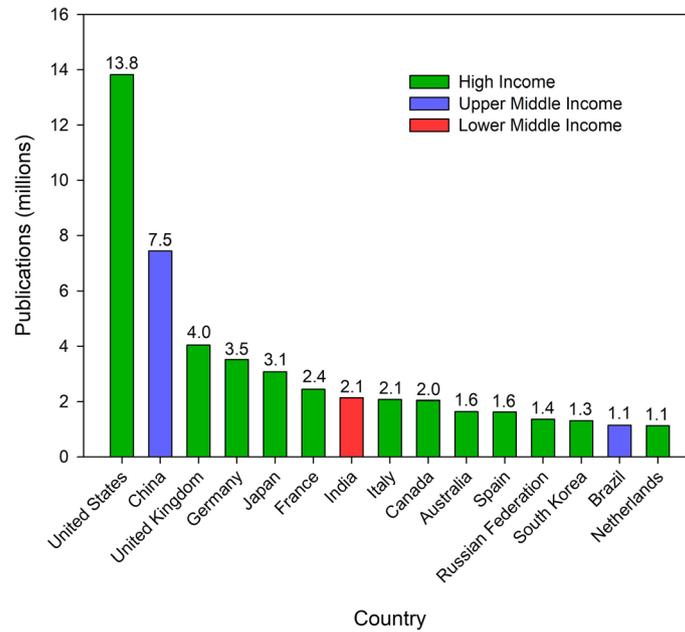


FIGURE 5 Top 15 most productive countries in all scientific fields for the 1996–2020 period (Source: Scimago).

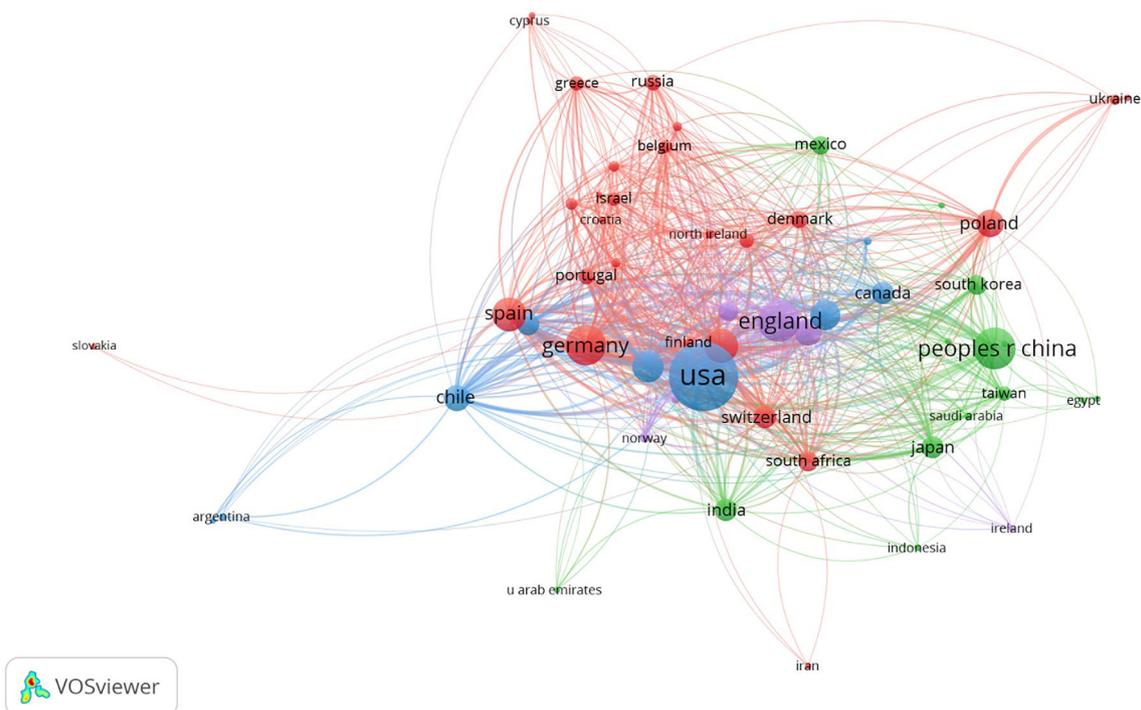


FIGURE 6 Map of co-authorships by country.

astrophysics. To this end, Figure 6 presents a map depicting co-authorship between researchers in different countries (with a minimum of three articles).

The colors represent clusters that are generated according to how often terms co-occur in a country; words that tend to co-occur more often are gathered into clusters. The sphere size reflects how many articles that country has published, and the line thickness represents the level of collaboration. The four countries that stand out as the most relevant are the USA, China, England, and Germany, leading the blue, green, violet, and red clusters, respectively, and showing a great level of collaboration within and between their clusters.

It appears that the co-authorship cluster structure primarily correlates with the respective geographical area and cultural and/or social affinity. In other words, primarily European countries occupy the red cluster (eventually with South Africa), while US authors are in the blue cluster. The violet cluster is associated with the United Kingdom and Ireland, and the green cluster comprises Asian countries and some collaborative efforts with Mexico and India. Based on this, we may assume that when researchers from different countries are co-authors, their collaboration is highly conditioned by factors including geographical closeness and cultural and linguistic similarity. For example, Spain plays a significant role as a research nexus linking Latin America with Europe.

On the other hand, in order to analyze the evolution over the years of the publications by country, Figure 7 is presented.

As can be seen, some countries appear to have more established research, for example, the United States, Mexico, and Poland, as they have bluer circles, meaning average publication dates that are 5 years older or more. Meanwhile, the most recent works come from the Nordic countries, for example, Finland and Norway, as well as countries like Belgium and Portugal; their circles in Figure 7 are yellow, meaning publication dates no more than 2 years ago. Finally, while it is comparatively less time-shifted, the research from Spain, Germany, and other European countries, as well as China and England, are in the 3–4 year range, that is, light blue to green.

3.2 | Topic analysis

VOSviewer was used to perform a topic analysis via semantic analysis, thereby creating a map showing the main subjects of interest, that is, relevant to the application of AI/ML to astronomy and astrophysics, and their relationships. Hereby, 4181 relevant keywords were initially identified in the WoS database; after setting the minimum threshold of

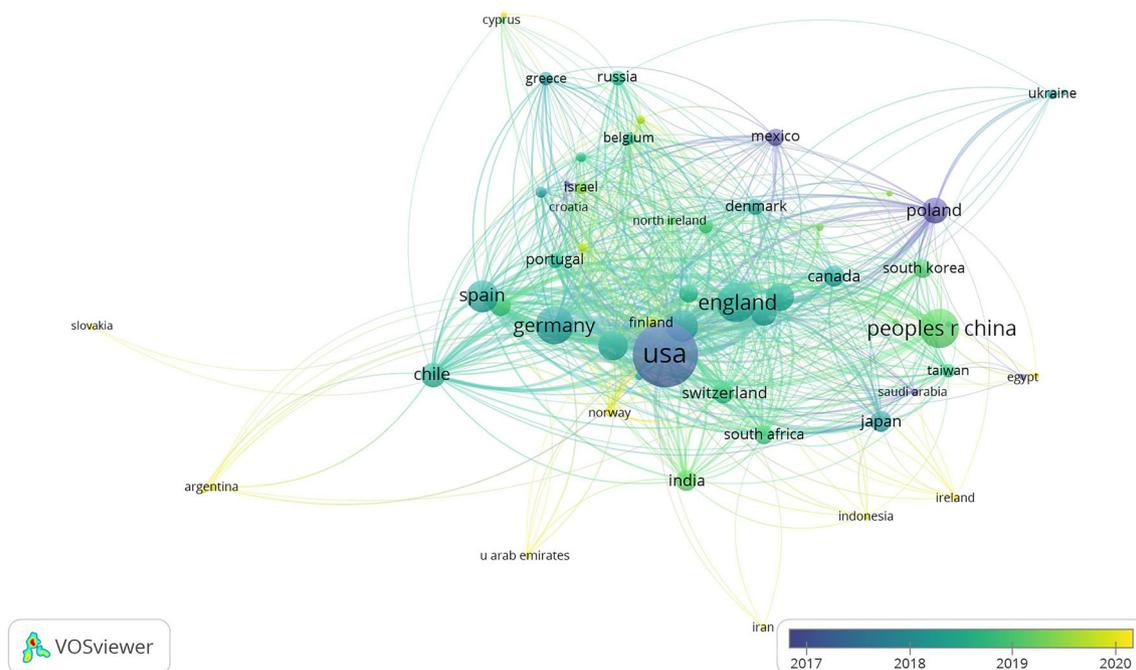


FIGURE 7 Mapping and visualization of the publications by country overlaid with the average publication year.

(Quinlan, 1986; Rokach & Maimon, 2008). The application of DTs to astronomy began in the 1990s, with tasks such as star-galaxy identification (Weir et al., 1995) to subsequently investigate the morphological classification of galaxies (Kriessler et al., 1998; Owens et al., 1996), predict the generation of solar flares (Ma et al., 2017), and estimate the redshift of quasars (Meshcheryakov et al., 2018). A further development of DT is the adaptive boosting (AdaBoost) method (Freund & Schapire, 1995), which consists of assigning weights to the contribution of each DT in such a way that previously misclassified data are given greater importance; this produces a new classifier that achieves better and more accurate results. AdaBoost has been used in astronomy for photometric redshift estimation (Hoyle et al., 2015), star-galaxy identification (Sevilla-Noarbe & Etayo-Sotos, 2015), star-quasar classification (Viquar et al., 2019), and light curve analysis (Edes-Huyal et al., 2021). An alternative use of DTs is gradient boosting (Friedman, 2001), a model that is formed by a set of individual DTs trained sequentially, wherein each new tree tries to improve the errors of the previous trees. The prediction of a new observation is thereby obtained by adding the predictions of all the individual trees that constitute the model. Gradient boosting has been applied to astronomy in fields such as star-galaxy classification (Morice-Atkinson et al., 2018), the prediction of solar wind (Bailey et al., 2021), and the identification of stars, galaxies, and active galactic nuclei (Golob et al., 2021).

The RF algorithm also arose as an extension of DT (Breiman, 2001) and consists of a group (ensemble) of DTs that are trained with different subsets of the data (a technique called bagging) in such a way that no tree considers all the training data. Thus, each tree is trained with different data samples for the same problem; by combining their results, some errors compensate for others, producing a prediction with better generalization. The use of RF in astronomy and astrophysics has been widespread since the 2000s, including in the analysis of outliers in astronomical images (Baron & Poznanski, 2017), predicting disruptive events in galaxies (French & Zabludoff, 2018), studying black hole growth (Goulding et al., 2018), detecting radio pulses (Pang et al., 2018), and classifying supernova (Ishida et al., 2019).

SVM encompass a classification technique that, given a supplied dataset, tries to find a hyperplane that allows the group to be divided into subsets following a certain decision criterion (Cortes & Vapnik, 1995). The aim is to find the hyperplane that provides the maximum separation between the data subgroups (support vectors). Also used since the 2000s, SVM have been applied in astronomy in areas such as detecting variable stars (Woźniak et al., 2004), estimating photometric redshifts (Wadadekar, 2004), identifying star-galaxies (Fadely et al., 2012), predicting the solar coronal mass (Liu et al., 2018), analyzing the physical properties of galaxies (Hui et al., 2018), and classifying evolved stars (Hernandez et al., 2021).

Finally, ANN, which constitute the basis of DL and were already proposed in the 1950s (Rosenblatt, 1957), can be considered the most powerful learning model within the field of AI and ML. ANNs, inspired by biological brains, comprise a set of units, called artificial neurons, which are connected to transmit signals. Thus, the input information crosses the neural network, where it is subjected to various operations weighted with the corresponding weights, producing output values. These systems learn and train themselves (rather than being explicitly programmed), and excel in areas where detecting solutions or characteristics is difficult to express using conventional programming. In the astronomical/astrophysical field, ANN first made an appearance in the 1990s in applications of adaptive optics for telescopes (Angel et al., 1990) and continued to find use in research fields such as the morphological classification of galaxies (Lahav et al., 1996), estimating photometric redshifts (Collister & Lahav, 2004), the search for cosmic strings (Ciuca & Hernández, 2017), the discovery of hypervelocity stars (Marchetti et al., 2017), identifying pulsars (Bethapudi & Desai, 2018), the analysis of neutron stars (Fujimoto et al., 2018), and predicting the parameters of stellar atmospheres (Azzam et al., 2021). CNN/DNN represent an evolution of ANN, as mentioned in the introduction, and have been used within the field of astronomy/astrophysics to morphologically classify galaxies (Huertas-Company et al., 2015), research transit objects (Gieseke et al., 2017), detect exoplanets (Pearson et al., 2018; Shallue & Vanderburg, 2018), and identify lens (Davies et al., 2019) and gravitational waves (Baltus et al., 2021).

Other terms that appear in this cluster, such as “computer vision” and “image processing,” refer to the methods used to process the millions of astronomical images that are produced every day (through, among other instruments, telescopes) and from which it is possible to obtain knowledge on the underlying physical processes (Müller et al., 2018) and determine the classification of the objects that appear (Ma et al., 2019). These methods are usually based on CNN (Dieleman et al., 2015; Hoyle, 2016) due to the power of this technique when classifying (Krizhevsky et al., 2012).

3.2.2 | Application of AI and ML in the field of stellar analysis (green cluster)

This group includes terms related to the study of stars within the scope of AI and ML applications. Two main lines of classification can hereby be distinguished: Photometric and spectral. Examples of AI/ML applications in the first can be

found in Dorn-Wallenstein et al. (2021), Ksoll et al. (2018), and Zhang et al. (2018) and, in the second, in Garcia-Dias et al. (2018), Miettinen (2018), and Sharma et al. (2020). The use of AI/ML in astronomy has led to the recent discovery of new star types, including hypervelocity stars (Marchetti et al., 2017), hot sub-dwarfs (Bu et al., 2019), Wolf-Rayet type stars (Morello et al., 2018), and unresolved binaries (Kuntzer & Courbin, 2017). In addition, AI/ML methods have also been used to obtain new knowledge and classification algorithms regarding neutron stars (Fujimoto et al., 2018; Tan et al., 2018).

Furthermore, as can be seen in Figure 8, the prevalent term “variable stars” also appears in the green cluster. These star types provide intense photometric information that is ideal for the application of AI/ML techniques to enable both classification tasks (Hosenie et al., 2019; Naul et al., 2018; Papageorgiou et al., 2018) and the development of new insights (Pashchenko et al., 2018; van Roestel et al., 2018).

Another field related to stellar astrophysics that appears in this group—through the terms “planets and satellites: detect” and “light curves”—is the detection of exoplanets and transit objects. In this regard, ML models have substantially improved the accuracy in identifying candidates for extrasolar planets (Armstrong et al., 2018; Jara-Maldonado et al., 2020; Mislis et al., 2018), determining their possible habitability (Basak et al., 2021; Saha et al., 2018), and evaluating the composition of their atmosphere (Hayes et al., 2020; Márquez-Neila et al., 2018). With regard to transit objects, AI has made it possible to accelerate their identification, especially in real-time applications (Bellm et al., 2019; Djorgovski et al., 2016; Sánchez et al., 2018).

In the area of “solar magnetic fields,” AI/ML is used to study the sun, for example, classifying and predicting solar flares (Abduallah et al., 2020; Benvenuto et al., 2018), anticipating coronal mass ejection phenomena (Liu et al., 2018; Tiwari, 2021), and predicting the number of sunspots in the next solar cycle (Panigrahi et al., 2021; Wang et al., 2021). Furthermore, AI/ML can also be applied within the solar system, for example, in the detection of trans-Neptunian objects (Chen et al., 2018; Henghes et al., 2020) or the classification of asteroids (Carruba et al., 2020; Erasmus et al., 2018).

Finally, another field of stellar astronomical research in which AI/ML methods can be applied in this cluster is “asteroseismology” or stellar seismology, where they can facilitate the study of the internal structure of pulsating stars based on their frequency spectra (Hon et al., 2017; Mackereth et al., 2021).

Study of cosmology using AI and ML methods (yellow cluster)

The yellow cluster groups the terms related to the application of AI/ML to cosmology. As demonstrated by the term “simulations,” this field of study works with mathematical models that use computer simulations to consider the corresponding initial conditions and gravitational physical mechanisms, generating a large volume of data (generally, relative to evolution processes) that can be used for prediction and analysis tasks (Poczós, 2018; Rodríguez et al., 2018; Villaescusa-Navarro et al., 2021). Other examples of areas of cosmology in which AI/ML find use are the study of dark matter (Bertone et al., 2017; Lucie-Smith et al., 2018; Stephon et al., 2020) and its halos surrounding galaxies (Agarwal et al., 2018; Lucie-Smith et al., 2019; Nadler et al., 2018), dark energy (Arjona & Nesseris, 2020a; Escamilla-Rivera et al., 2020), models of the creation and expansion of the universe (Arjona & Nesseris, 2020b), the cosmic microwave background (CMB) (Arjona, 2020; Mishra & Reddy, 2020), and the total mass of galaxies (considering dark matter) (McLeod et al., 2017). At this point, generative adversarial networks (GAN) are worth mentioning; since they are capable of simplifying, or even eliminating, the use of costly simulations in cosmology, they constitute one of the most promising ML models in astronomy/astrophysics (Diakogiannis et al., 2019).

Another field of application of AI/ML in cosmological analysis, as indicated in this cluster by the term “gravitational lensing,” is the study of gravitational lenses. In this sense, beyond the discoveries produced by AI/ML in this field (Mirzoyan et al., 2019; Ostrovski et al., 2017; Teimoorinia et al., 2020), it should be mentioned that one of the obstacles in applying DL in the search for this peculiar astrophysical phenomenon is the scarcity of data with which to carry out the training phase. For this reason, simulated lenses are often used, usually on a galactic scale. This has allowed gravitational lenses to be detected from data originating from various astronomical sources (Magro et al., 2021; Metcalf et al., 2019; Petrillo et al., 2019; Schaefer et al., 2017).

Finally, it is also worth highlighting the scope of application of AI/ML to cosmology through the analysis of gravitational waves, recently detected (Abbott et al., 2018) thanks to the Advanced Laser Interferometer Gravitational-Wave Observatory (LIGO) (Harry & LIGO, 2010). Through the use of ML, it has been possible to improve detection by discarding noise in a more efficient way (Powell et al., 2017; Vajente et al., 2020).

3.2.3 | Analysis of galaxies by means of AI and ML techniques (blue cluster)

Finally, the blue group refers to terms related to the use of AI/ML methods in the study of galaxies. Indeed, one of the most widespread applications of AI/ML in astronomy has been in galaxy classification (Beck et al., 2018; De Diego et al., 2020; Domínguez Sánchez et al., 2018; Nolte et al., 2019). Notably, automatic galactic classification has undoubtedly been accelerated thanks to the previous (visual) classifier work carried out by numerous volunteers in the Galaxy Zoo project (Lintott et al., 2008) (note the term “zoo” in this cluster).

In addition to classification tasks, there are other applications of AI/ML to the analysis of galaxies, such as estimating their physical properties (Rafieferantsoa et al., 2018; Ucci et al., 2017) (“galaxies: structure”), their rate of star formation (Delli et al., 2019) (“galaxies: star formation”), the evolution of their discs (Forbes et al., 2019) (“galaxies: evolution”), their kinematics (Dawson et al., 2020; de los Rios et al., 2021), and their photometric redshifts (Bilicki et al., 2018; Razim et al., 2021; Zhang et al., 2020) (“galaxies: photometry”).

Finally, the presence of the terms “active galactic nuclei” and “quasars” is notable within this group; these refer to the ML astronomical application that addresses the morphological classification of nuclei of active galaxies (Chang et al., 2021; Chen et al., 2020; Ma et al., 2019) and the analysis of gamma-ray emissions arising from these (Fidor & Sitarek, 2021) as well as the detection of quasars (Herle et al., 2020; Jin et al., 2019; Schindler et al., 2017) and blazars (Kang et al., 2019; Mao et al., 2020; Sversut & Neto, 2020).

3.3 | Topic variation over time

Following the topic analysis and the delineation of the clusters and affinities of the topics, Figure 9 presents an overlay visualization that superimposes each topic's average date of publication from 2015 onwards. This sheds light on both the more established lines of research in this field and which topics are receiving the most research attention (*hot topics*, defined as subjects currently of great interest). The blue circles in the figure refer to the start of the five-year period under investigation, while the green and yellow circles are more recent.

This technique was designed to enable observations to be made on how research has evolved over decades; however, in this work, the time span has been limited to 5 years because of the explosive growth in this topic in recent years, as highlighted in Figure 1.

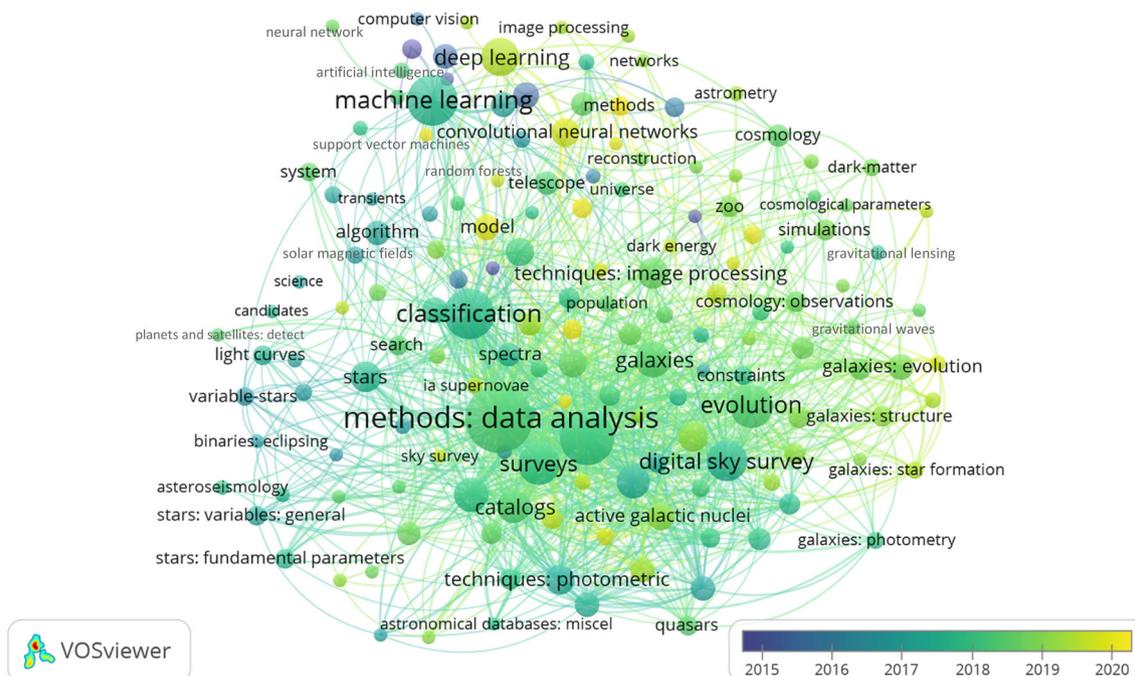


FIGURE 9 Mapping and visualization of the topics overlaid with the average publication year.

As can be seen, the cluster related to AI/ML applications in the analysis of stars (green in Figure 8) seems to be the most established of the four identified in Figure 8 as the topics that form it generally appear bluer, that is, have average publication dates in the first half of 5-year period. It should be noted that the great potential of AI/ML in the astronomical field was first realized in spectral and photometric stellar classification, among others.

On the other hand, the cluster on the use of AI/ML in cosmology (yellow in Figure 8) is the most recent in Figure 9 as the topics comprising it are, in general, green or yellow (within the last 2–3 years). Clearly, AI/ML is providing new methods to analyze the data produced through cosmological simulations to the extent that this line of research is at the forefront of the application of AI/ML in astrophysics. AI/ML thus provides knowledge on the evolution of the universe and its structure, including the study of dark matter and dark energy as well as the interstellar environment.

For its part, the cluster referring to the study of galaxies using AI/ML (the blue group in Figure 8) comprises topics that, while not being the most time-shifted, do represent a range spanning the last 3–4 years (from light blue to yellow). In this sense, research areas such as the application of AI/ML to galactic classification through photometry appear as the most established (bluer), while other fields, such as the analysis of the evolution and structure of galaxies or active galactic nuclei, emerge as pioneers (more green-yellow).

Finally, with topic colors ranging from blue to yellow, the cluster related to the different AI/ML techniques that are applied in the fields of astronomy/astrophysics (the red group in Figure 8) is the most distributed in Figure 9 in terms of publications over the last 5 years. This relates to the progression of the application of the various AI/ML techniques in astronomy and astrophysics, ranging from the most established (“computer vision”) to the most innovative (“convolutional neural networks”).

To further delve into this analysis, Figure 10 presents a specific graph showing how the prevalence of the five main AI/ML methods applied to astronomy/astrophysics problems has changed over the years (from 2010 to the present).

As can be observed, the use of ANN has been prioritized, experiencing dramatic growth in the last 5 years. Notably, the use of CNN has similarly grown substantially since 2015, when they first emerged (as mentioned above, CNN are an evolution of ANN). Meanwhile, SVM was the next most-used method until 2019, when it was overtaken by RF and later, PCA. It is worth noting that, although PCA is a technique used to reduce the dimensionality of datasets before the application of various ML prediction or classification algorithms, due to its prevalence since the 1960s within astrophysics, such as for stellar spectrum, galaxy or quasar classification, we include the PCA curve in Figure 10, bearing in mind that this curve should be interpreted as the number of publications that use PCA in combination with other—more strictly speaking—ML methods. Finally, DTs have seen discreet yet regular use over the years.

Figure 11 presents a map of the main AI/ML techniques applied to astronomy/astrophysics (the five main ones already mentioned, along with some additional methods based on the keywords) overlaid with the average publication year (since 2011).

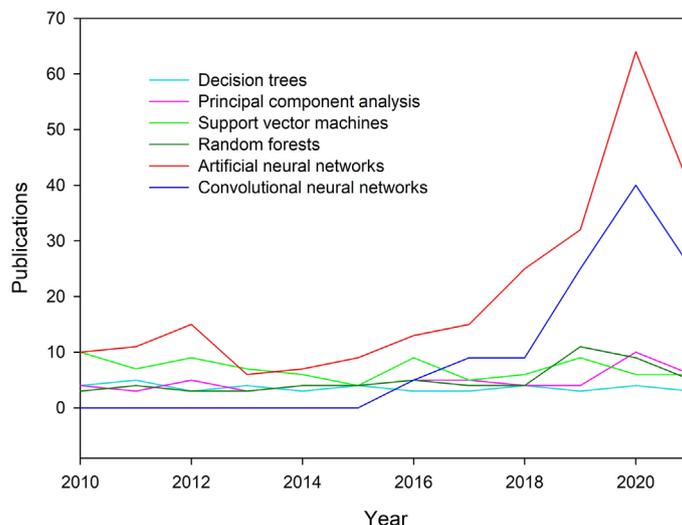


FIGURE 10 Timelines of the publications regarding the main ML/AI methods applied.

Clearly, the number of citations has skyrocketed in recent decades, especially since 2005. The citations hereby display an exponential behavior that is directly related to the recent dramatic growth in the number of publications in the field under study (as already observed in Figure 1).

The following presents a more detailed study of the citations (by source and author) as well as an analysis of the most cited publications.

3.4.1 | Citation by source

As a preliminary step to studying the citations according to their source, it is interesting to analyze the most productive sources in this field. Table 3 lists the 15 sources with the most publications.

The two journals with the highest number of publications are *Astronomy & Astrophysics* and *Monthly Notices of the Royal Astronomical Society*. Two additional large groups of sources are observed, namely those dedicated to general astronomy and astrophysics, and those focused on the application of computing to astronomy.

Meanwhile, to facilitate a source-based analysis of the citations, the 15 most-cited journals were taken from WoS (Table 4).

Several journal types in certain categories become immediately visible, namely journals dedicated to astronomy and astrophysics, multidisciplinary journals, journals on computing, and journals on the earth and physics. Although the presence of the journal *PLoS Biology* might be surprising, its inclusion in this list is motivated by publications that analyze the relationship between the behavior of ANN and biological neurons. In any case, the first places on the list are occupied by journals specializing in astronomy and astrophysics. It should be noted that *Big Data, Little Data, No Data: Scholarship in the Networked World* is actually a book.

The results show that with 7691 citations, *Astronomy & Astrophysics Supplement Series* was the most cited journal, followed by *Monthly Notices of the Royal Astronomical Society* with 5412 citations and *Astronomy & Astrophysics* with 5358 citations. Notably, while certain journals were very frequently cited by numerous publications on the topic, others produced a vast number of citations, yet were actually cited by far fewer articles.

Lastly, 4 of the 15 selected journals were open access (*Astrophysical Journal*, *Astrophysical Journal Supplement Series*, *PLoS Biology*, and *Scientific Reports*), although some of the others also avail of this publication channel.

TABLE 3 Top 15 most productive sources

Source	No. of publications
Astronomy & Astrophysics	344
Monthly Notices of the Royal Astronomical Society	331
Proceedings of SPIE	211
Astrophysical Journal	158
Astronomy and Computing	83
Astronomical Journal	72
Research in Astronomy and Astrophysics	63
Astronomical Society of the Pacific Conference Series	59
EPJ Web of Conferences	54
Library and Information Services in Astronomy	46
Astrophysical Journal Supplement Series	45
Astrophysics and Space Science	40
Lecture Notes in Computer Science	34
Chapman Hall CRC Data Mining and Knowledge Discovery Series	33
Science China Physics Mechanics Astronomy	33

3.4.2 | Most cited publications

Table 5 lists the 15 publications with the most citations within the scope of AI/ML applications in astronomy and astrophysics.

The article “SExtractor: Software for source extraction,” published in the journal *Astronomy & Astrophysics Supplement Series* and presenting software that automatically detects and classifies sources (stars, galaxies, etc.) from

TABLE 4 Top 15 most cited sources

Publication title	Citations
Astronomy & Astrophysics Supplement Series	7691
Monthly Notices of the Royal Astronomical Society	5412
Astronomy & Astrophysics	5358
Astrophysical Journal	2306
Astrophysical Journal Supplement Series	1000
Annals of Applied Statistics	597
PLoS Biology	577
Nature	577
Annual Review of Astronomy and Astrophysics	348
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	327
Big Data, Little Data, No Data: Scholarship in the Networked World	286
Scientific Reports	164
International Journal of Modern Physics D	155
International Journal of Climatology	147
Scientia Iranica	121

TABLE 5 Top 15 most cited publications

Title	Publication date	Citations
SExtractor: Software for source extraction (Bertin & Arnouts, 1996)	Jun 1996	7509
A correlated topic model of science (Blei & Lafferty, 2007)	Jun 2007	597
Big data: Astronomical or genetical? (Stephens et al., 2015)	Jul 2015	558
Genetic algorithms in astronomy and astrophysics (Charbonneau, 1995)	Dec 1995	538
Image reconstruction by domain-transform manifold learning (Zhu et al., 2018)	Mar 2018	473
Adaptive optics for astronomy—principles, performance, and applications (Beckers, 1993)	Jan 1993	348
Rotation-invariant convolutional neural networks for galaxy morphology prediction (Dieleman et al., 2015)	Jun 2015	314
Big data, little data, no data: Scholarship in the networked world (Borgman, 2015)	Jan 2015	286
Imaging the Schwarzschild-radius-scale Structure of M87 with the event horizon telescope using sparse modeling (Akiyama et al., 2017)	Mar 2017	227
A kernel-based feature selection method for SVM With RBF kernel for hyperspectral image classification (Kuo et al., 2014)	Jan 2014	179
A Gaussian process framework for modeling instrumental systematics: application to transmission spectroscopy (Gibson et al., 2011)	Jan 2012	170
Gaia early data release 3 summary of the contents and survey properties (Brown et al., 2021)	Apr 2021	160
Machine learning quantum phases of matter beyond the fermion sign problem (Broecker et al., 2017)	Aug 2017	159
An asteroseismic view of the radius valley: Stripped cores, not born rocky (Eylen et al., 2017)	Oct 2018	156
Data mining and machine learning in astronomy (Ball & Brunner, 2010)	Jul 2010	155

astronomical images, leads the *ranking* very clearly, with 7509 citations. As expected, the first positions of the table tend to be occupied by older publications. Meanwhile, it is possible to identify groups of publications that cover both generic topics of the application of AI/ML techniques to astronomy/astrophysics and more specific questions related to classification/prediction methods or astronomical observation campaigns.

3.5 | Co-citation analysis

The statistical technique of co-citation analysis enables the idle relationships between journals and/or authors to be detected and then visually expressed as co-citation clusters, thereby elucidating the meaning of this information. This method is derived from the assumption that articles by certain co-cited researchers or journals tend to tackle concepts that are similar or at least related. Co-citation refers to the instance when two separate publications are cited by a third.

3.5.1 | Co-citation by source

In Figure 13, the co-citations map (a minimum of 20 co-citations, which led to 237 sources) is shown as a function of the publication source, for articles related to the application of AI/ML to astronomy/astrophysics.

Regarding the co-citations according to their source (generally, a journal), these occur in four clusters, as described in the following.

The green cluster (which has the highest prevalence) refers to generic journals in the field of astronomy and astrophysics, for example, *Monthly Notices of the Royal Astronomical Society* (9543 co-citations) and *Astrophysical Journal* (8843 co-citations), had already appeared in the first positions of Tables 3 and 4, that is, had the highest number of publications and citations, respectively. Based on the size of the items in this group, the main journals in this cluster appear to be the most co-cited options within the research field under analysis.

The red cluster group comprises journals whose scope is the AI/ML field (*Journal of Machine Learning Research*, with 534 co-citations, *Machine Learning*, with 435 co-citations, or *IEEE Transactions on Pattern Analysis and Machine Intelligence*, with 173 co-citations) or its application to astronomy (*Astronomy and Computing*, with 292 co-citations). As a special case in this group, the journal *Nature* appears in red (923 co-citations); as the general

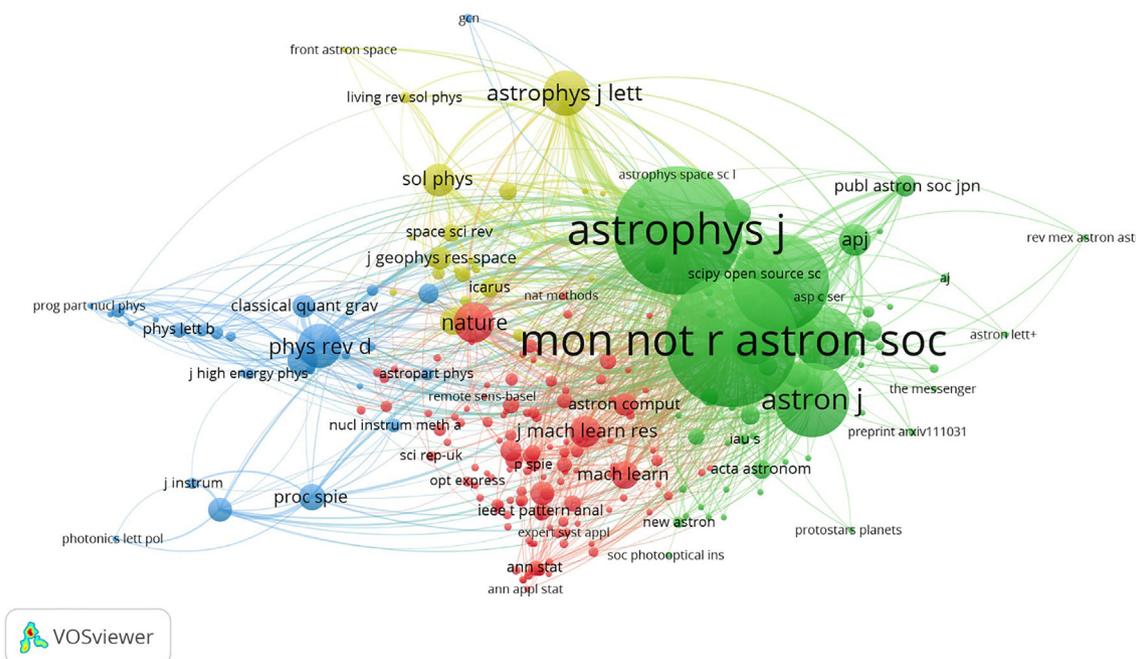


FIGURE 13 Map of co-citation by source.

reference journal within the scientific field, and considering that it is near the center of the map, it could be drawn in the color of any of the clusters.

The blue cluster represents the journals focused on the field of general physics, such as *Physical Review D* (1093 co-citations) and *Physics Letters B* (132 co-citations), or on the physical phenomena underlying astronomy and astrophysics, such as *Proceedings of SPIE* (388 co-citations), *Classical and Quantum Gravity* (302 co-citations), and *Journal of High Energy Physics* (77 co-citations).

Finally, the yellow cluster refers to sources focused on the study of space or the space environment, such as the *Journal of Geophysical Research: Space Physics* (293 co-citations) and *Space Science Reviews* (179 co-citations), or, specifically, on solar astrophysics, such as *Solar Physics* (584 co-citations) or *Living Reviews in Solar Physics* (71 co-citations). It should be noted that this group also contains the journal *The Astrophysical Journal Letters* (1133 co-citations); although it addresses general issues in astrophysics, with regard to co-citations, it seems to be prevalent in questions relating to the space environment or solar astrophysics.

3.5.2 | Co-citations by author

Examining co-citations can clarify the relationships between the authors. Specifically, co-cited authors likely have a connection of some kind, for example through a common subject, discipline, affiliation, or country of origin.

Before analyzing the map of co-citations by author, it is interesting to show the most productive authors in terms of publications related to the application of AI/ML to astronomy/astrophysics. As such, Table 6 contains the 15 authors with the most publications.

The table is led by Professor Ping Guo from Beijing Normal University, China, with 35 publications focused especially on the application of different AI/ML techniques to the classification of astronomical objects and phenomena (Qin et al., 2003; Wang et al., 2016). The next is researcher Yian-Xia Zhang from the CAS Key Laboratory of Optical Astronomy, National Astronomical Observatories, Chinese Academy of Sciences, Beijing, China, with 33 publications primarily focused on the application of ANN to the estimation of redshifts (Han et al., 2020; Li et al., 2021). In third place is researcher Yong-Heng Zhao, also from the Key Laboratory of Optical Astronomy, National Astronomical Observatories, Chinese Academy of Sciences, Beijing, China, with 30 publications on the application of AI/ML to the classification of stars (Li et al., 2017; Wang et al., 2020). This highlights the prevalence of Chinese authors in the field of applying AI/ML to astronomy/astrophysics. It should be noted that Professor Giuseppe Longo from the Università

TABLE 6 Top 15 most productive authors

Authors	No. of publications
Guo, P.	35
Zhang, Y. X.	33
Zhao, Y. H.	30
Longo, G.	30
Bertin, E.	25
Brescia, M.	23
Cavouti, S.	22
Kind, M. C.	22
Ishida, E. E. O.	21
Djorgovski, S. G.	20
Smith, M.	20
Yin, Q.	20
Yu, C.	20
Brooks, D.	19
Carretero, J.	19

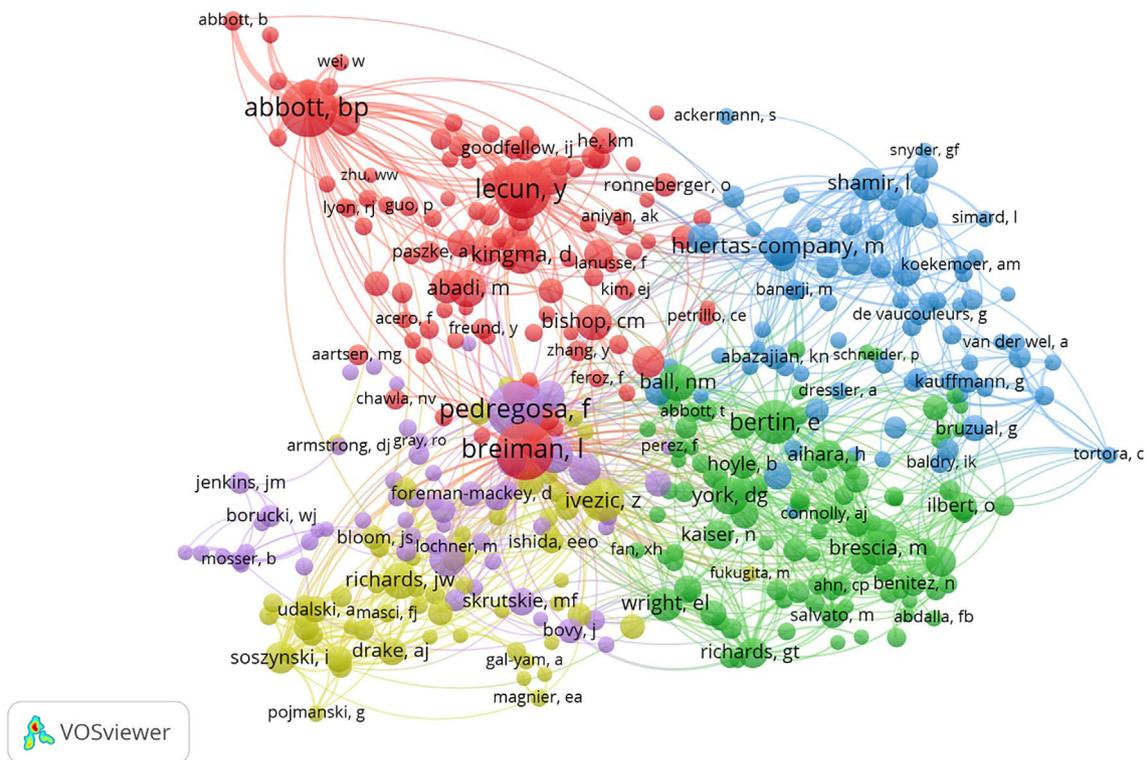


FIGURE 14 Map of co-citations by author.

Federico II, Napoli, Italy, ties for third place, with 30 publications focusing on the use of AI/ML for the estimation of photometric redshifts (Bilicki et al., 2018; Razim et al., 2021).

Figure 14 shows the map of co-citations per author (a minimum of 20 co-citations, which led to 410 authors), in which five clusters can be distinguished; these are described below.

The red cluster comprises authors who focus on the analysis and development of AI/ML techniques that are ultimately applied to the field of astronomy. In this sense, it is worth highlighting researcher Leo Breiman (271 co-citations) from the University of California, who is an RF expert (Breiman, 2001); Professor Yan Lecun (257 co-citations) from the New York University, who specializes in DL (LeCun, 2018); researcher Diederik P. Kingma (123 co-citations) from the University of Amsterdam, who focuses on ANN (Salimans & Kingma, 2016); and Christopher M. Bishop (108 co-citations) from the University of Edinburgh, who specializes in pattern recognition using ML (Bishop, 2010).

The violet group contains authors focused on the application of AI/ML in the search for exoplanets, such as William J. Borucki (43 co-citations) from the California Institute of Technology (Borucki et al., 2010); Jon M. Jenkins (40 co-citations) from the NASA Ames Research Center (Ansdell et al., 2018); and Benoit Mosser (32 co-citations) from the Observatoire de Paris: Laboratory for Space Studies and Instrumentation in Astrophysics (Nielsen et al., 2020).

The yellow cluster includes authors specialized in the use of AI/ML in stellar analysis, such as Joseph W. Richards (106 co-citations) from the University of California (Richards et al., 2011); Professor Igor Soszynski (83 co-citations) of the Astronomical Observatory of the University of Warsaw (Soszyński et al., 2018); and Andrew J. Drake (66 co-citations) from the California Institute of Technology (Mahabal et al., 2017).

The green group includes authors exploring the use of AI/ML to study the physical properties of the space environment and astronomical objects, such as Emmanuel Bertin (162 co-citations) from the Institut d'Astrophysique de Paris (Morgan et al., 2020); Donald G. York (117 co-citations) from the University of Chicago (Fan et al., 2019); and Massimo Brescia (98 co-citations) from the INAF Astronomical Observatory of Capodimonte, Naples (Davide et al., 2017).

Finally, the blue cluster groups authors who investigate the application of AI/ML to study galaxies, such as Marc Huertas-Company (123 co-citations) from de la Université de Paris (Cheng et al., 2021); Lior Shamir (95 co-citations) from Kansas State University Computer Science (Kuminski & Shamir, 2018); and Guinevere Kauffmann (47 co-citations) from the Max Planck Institute for Astrophysics (Grand et al., 2019).

4 | CONCLUSION

This work presented a text-mining-based scientometric analysis of the scientific output in the last three decades regarding the use of AI and ML in the fields of astronomy and astrophysics. Using the VOSviewer software and considering WoS as the data source, the study explored the evolution of publications in this research field, their distribution by country (including co-authorship), the most relevant topics addressed, and the most cited elements—as well as the most significant co-citations—according to the publication source and authorship.

In view of the obtained results, it can be stated that the scientific output on the application of AI/ML to astronomy/astrophysics has experienced exponential growth in recent years, especially since 2005, with the *Astronomy Astrophysics* category of WoS clearly emerging as the most prolific. Furthermore, publications have especially concentrated in the United States, China, and the United Kingdom—three of the strongest global economies. Meanwhile, four countries lead the co-authorship type of collaboration, namely the United States, China, the United Kingdom, and Germany.

Regarding the analysis of the main topics addressed in the scientific output of this field, four main lines of research have been identified, and these are the application of AI/ML techniques to astronomy/astrophysics, the application of AI/ML to analyze stars, the study of cosmology using AI/ML methods, and the analysis of galaxies using AI/ML. The second topic is the most established (stars), while the third is the most recent (cosmology).

The number of citations of publications on the application of AI/ML to astronomy/astrophysics has experienced a marked increase in recent decades, especially since 2005. The journal *Astronomy & Astrophysics Supplement Series* leads this ranking.

Finally, the number of co-citations mapped by source is headed by generic journals in the field of astronomy and astrophysics, namely *Monthly Notices of the Royal Astronomical Society* and *Astrophysical Journal*, while researcher Leo Breiman leads this category according to the author-based mapping.

In short, this work has shown how the application of AI and ML to the fields of astronomy and astrophysics is an already established and yet also significantly growing research field that is crucial to obtaining scientific knowledge about our universe. As AI techniques are in constant development, thus precipitating increasingly rapid and sophisticated methods, the potential for their future use in making new astronomical discoveries seems unimaginable. In light of this, our future research will further pursue the analysis of this fascinating topic through bibliographic and statistical methods. The aim here is to offer a more nuanced understanding of this area concerning how researchers collaborate, how scientific production has progressed, and which research trends are prevalent in this area.

AUTHOR CONTRIBUTIONS

José-Victor Rodríguez: Conceptualization (lead); data curation (lead); formal analysis (lead); funding acquisition (equal); investigation (lead); methodology (equal); project administration (equal); resources (lead); software (equal); supervision (equal); validation (equal); visualization (equal); writing – original draft (lead); writing – review and editing (lead). **Ignacio Rodríguez-Rodríguez:** Conceptualization (equal); data curation (equal); formal analysis (equal); funding acquisition (equal); investigation (equal); methodology (equal); project administration (equal); resources (equal); software (equal); supervision (lead); validation (equal); visualization (equal); writing – original draft (equal); writing – review and editing (equal). **Wai Lok Woo:** Conceptualization (equal); data curation (equal); formal analysis (equal); funding acquisition (equal); investigation (equal); methodology (equal); project administration (equal); resources (equal); software (equal); supervision (lead); validation (equal); visualization (equal); writing – original draft (equal); writing – review and editing (equal).

CONFLICT OF INTEREST

The authors have no competing interests to declare that are relevant to the content of this article.

DATA AVAILABILITY STATEMENT

All the data is available at Web of Science. <https://www.webofknowledge.com>.

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