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IoT Devices With Data Analytics Capabilities Using Machine Learning Algorithms For Intelligent Decision Making: A Review Of Patents And The Cited Academic Literature

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ABSTRACT

Innovation in IoT data analytics is essential for social and economic advancement as well as for opening up new business prospects. IoT data analytics applications have garnered a lot of attention lately for information mining, knowledge extraction, and prediction/inference making. Another field of study that has been effectively used to address a variety of networking issues, including resource allocation, routing, traffic engineering, and security, is machine learning. The use of machine learning (ML)-based techniques to enhance different Internet of Things applications has increased recently. Despite a wealth of research on machine learning and IoT data analytics, there is a dearth of studies that only address the development of ML-based methods for IoT data analysis. The present study examines the patenting practices of various international jurisdictions in the domain of analytics for IoT data, in addition to the academically cited literature. Between 2000 and 2023, we gathered 24,931 patent applications, and 13,432 academic publications were referenced in the patents. Our research details the trends in the development of IoT data analytics technologies and the relationship between patenting activity and the referenced scientific literature. Additionally, it examines and displays the social networks found in scientific publications and patents. As a result, it discloses the patenting practices of international jurisdictions concerning IoT data analytics technologies, the extent to which various agents, such as Lens Id and Applicants, interact in social networks, and the relationship between patents and science. Based on this study, the majority of IPC categories for filed IoT data analytics patent applications include information retrieval, database structures, and file system structures. US businesses and individuals make up the bulk of the patent Lens Id and Applicants. Computer science and medicine are scientific fields that are more strongly connected within the network of co-fields. The relationship between scientific works and inventions is not very strong.

Keywords: IoT data analytics, Patent analysis, Bibliometric analysis, Social network analysis, Innovation evolution, Citation linkage, Technological development trend.

1. Introduction

As a result of the quick development of technologies that can generate large volumes of data, there has been a global push to create solutions for improved IoT data analytics processing, storage, and analysis. IoT data analytics is thought to be essential to the social and economic advancement of organizations and communities [1]. Customers are producing more data about their attitudes and behaviours as a result of social media's growing usage and machine subordination. In the debt economy, this data is tradable and purchasable like commodities, and it can be utilized for marketing and other commercial endeavours [2]. An increasing number of organizations are shifting toward becoming data-driven enterprises as companies that self-identify as such appropriately concentrate on "objective measures of financial and operational results"[3]. Over 80% of technology-related knowledge is protected by patents [4]. Numerous uses for this data exist, including identifying market trends and forecasting future advancements in technology.

The IoT data analytics market is expected to generate $103 billion in revenue globally in 2027 from $42 billion in 2018 in the software and service sectors alone, according to estimates [5]. This indicates that the IoT data analytics industry is expanding and has new prospects. In 2014, the UK government identified "eight great technologies" that will drive economic growth in the nation, including IoT data analytics [6]. IoT data analytics is a very broad field that includes innovations in open sources, APIs, data sources, analytics, applications, and infrastructure, according to Matt Truck Company. Numerous IoT data analytics innovations have been introduced globally as a result of the field's expanding landscape and growing impact on global development. As a result, it's critical that both academia and business understand the new trends in IoT data analytics technologies, which are crucial to the development of data-driven businesses. While very few studies have evaluated IoT data analytics innovations across jurisdictions, to our knowledge, not much academic work has been done to paint a comprehensive picture of the creative IoT data analytics initiatives of businesses and nations over time. The purpose of this paper is to provide a comprehensive overview of the evolution of Internet of Things (IoT) data analytics technology, tracking and describing its trends over time and across legal domains, as well as describing its interactions and relationships with science.

Analysing patent data can help us better understand the dynamics and activities of the invention ecosystem. It is believed that measures of innovation based on outcomes are found in patent data, reflecting advances in science and technology as well as creative processes [7]. They can also be used to evaluate technology management [9, 10] or “appropriately” describe how a technology is spreading [8].

However, some research highlights the fact that patent data does not capture the whole ecosystem of inventions; Scientific literature is one example of an alternative information source that needs to be mentioned [7–11]. Innovation systems development requires interactions between universities and industry [12], and it is recommended that inventors include citations to scientific publications in their patent applications [13]. Several jurisdictions require applicants to provide a comprehensive and comprehensible description of their invention, including prior art any invention that has been made public before being filed by anyone, anyplace in the world, utilizing any technique priority data. As a result, it is expected that the patent documents will describe the technical aspects of the invention as well as recent academic and scientific developments in the relevant industry; thus, patent data may also represent scientific advances in technology.

Through the use of patent data, quantitative techniques like bibliometric and social network analysis can identify Secret motifs in the innovation landscape and uncover technological trends and their correlation with scientific data. This allows for the extraction of predictive insights about a technology's development [14]. Previous studies indicate that social network analysis is a more effective data mining visualization technique [15] than other conventional methods [16]. In particular, the social network analysis locates connections and associations (edges) among participants (nodes). Nodes during a patent examination stand in for people, like Lens Id and Applicants, or things, like patent documents or subject areas. Their cooperative activities, like their citation links, can also be the edges between the nodes [17]. It is possible to analyse similarities and differences between actors in low-dimensional spaces on multiple dimensions using social network analysis. The actors in this method are more distant in space from among themselves within the input data, and they are spatially closer together. from each other in the less similar actors [18].

In order to examine patent applications, this study used bibliometric and social network visualization techniques. To examine scientific trends in a range of subjects, bibliographic analysis is integrated [19, 20]. Our objectives are to: (1) examine the temporal evolution of IoT data analytics patent productivity; and (2) evaluate the productivity of the IoT data analytics industry by identifying the most successful writers, candidates, regions, and establishments, businesses, patent classifications, and scientific fields of study. We will accomplish these goals by applying descriptive bibliometric analysis techniques; and (3) quantify the relationship between patents and scholarly works in the scientific domain. By employing social network analysis methods, our objectives are to: (4) examine and illustrate the relationships and exchanges among the networks of Lens Id, Applicants, Inventors, Scientific fields of study and keywords that appear in them and (5) show trends and patterns in patents within the scientific and creative IoT data analytics communities.

As of November 15, 2023, 13,432 scientific journals cited in 24,391 patents were analysed in order to track the developments in IoT data analytics technologies, according to data from the Lens Patent Website. Utilizing bibliometric and social network analysis techniques, the following outcomes were obtained: (1) a descriptive bibliometric analysis of patents and the academic works cited; (2) a citation linkage analysis of patents to academic works; (3) a social network analysis of invention activities associated with analytics for IoT data; and (4) a social network examination of academic publications referenced in patents related to IoT data analytics.

Prior research on patent analysis has proposed a wide range of analysis and visualization techniques, such as neural network analysis [24–26], semantic analysis [22, 23], and natural language processing [21]. Furthermore, a few previous studies combined patent citation data with external data [11, 27–29]. Previous studies on the topic of patent analysis for IoT data analytics technology looked at a variety of subjects, such as the analysis of Chinese IoT data analytics patent abstracts [30], hot classified IoT data analytics fields [31], quantitative patent analysis technology valuation methods for technology transfer in IoT data analytics marketing in Europe [32], and IoT data analytics-related business interests and activities.

This paper comprises the following sections: Firstly, a summary of previous studies that used patents to perform bibliometric analysis. The methods, procedures, analytical strategies, and instruments we used for our research are then covered in great detail. Our analysis's findings and conclusions are described in the following section. In conclusion, we discuss the research limitations, theoretical and practical implications of the paper, the conclusions, and possible future directions.

2. Conceptual structure

2.1 Patents as a metric for assessing innovation

Among the categories for assessing innovation are output-based indicators [34, 35]. The outcomes of innovative endeavours, like patents, comprise these metrics. Data from patents is a priceless tool for comprehending the innovation's dynamics and activities ecosystem. A useful tool for modelling and explaining the international growth of inventions is patent data, which provides companies, engineers, innovators, and decision makers with informative windows [36–38]. It is possible to "appropriately" describe the spread of a technological innovation [8] or evaluate technological oversight [9, 10] using data on patents, which are markers of inventive processes and changes in technology-science [7]. An inventive activity must be new, sufficiently described, and claimed for a patent to be considered an intellectual property right. Patents also link to prior art, such as scientific publications. Every person, business, academic institution, or other public or private enterprise may be granted a patent for their creative work [40].

Novelty is one of the primary prerequisites for an invention to be protected. Members of the TRIPS Agreement are obliged to send in applications that match new, creative, and have the potential for industrial use [41]. However, the term "novelty" is not defined in the agreement. Therefore, the Member Governments now have the authority to define novelty. For instance, novelty in Iranian law refers to an invention that was not anticipated by previous work. Section 4 of Iran's 2008 Trademarks, Patents, and Industrial Designs Act defines "previous work" as anything that has been disclosed in any form or by any means before the date of application or priority date, whether orally or in writing, through practical use, or in any other manner, anywhere in the world. Therefore, the prior art encompasses both scholarly works and patent applications in this broad sense. The invention would lose its novelty if it were published in scientific publications, and as a result, it would not be eligible for patent protection [42]. For this reason, certain legal systems mandate that the applicant attach an explanation of the invention to one of the application's supporting documents. Nonetheless, there is opposition to the idea that patents adequately capture the scope of innovation [43]. Some studies indicate that some innovations are not eligible for patent protection [7]. Furthermore, patents for innovations are not always indicative of innovations or the economic value of the new technical knowledge they contain [44]. Additionally, different countries and organizations might value patenting activities differently [45].

The 2008 amendment to Article 22 of the patent legislation in China, for instance, declares that "existing technologies mean the technologies known to the public both domestically and abroad before the date of application" and that "novelty means that the invention or utility model concerned is not an existing technology." According to Article 36 of the legislation, the applicant must submit the invention's reference materials in the event that they seek a substantive review. No application has yet been declared void, invalid, or withdrawn by the Chinese Patent Office as a result of information not being disclosed [46]. Conversely though, in China, withholding information is not against the law. Nonetheless, since omission of the patent could eventually result in its unenforceability, the US Patent Examining Procedure Manual Chapter (PEPM) 2000 addressed the disclosure obligation in substantial detail. For scientific works, the European Patent Office's background art has the highest reference rate; therefore, the description must include it, in accordance with European Patent Article 42 Convention. Failure to do so may result in the rejection of the application (Article 97) or the revocation of the patent (Article 101). According to All patent descriptions falling under the purview of WIPO are required to include references to prior art data, as stipulated by the Patent Cooperation Article 5 Treaty.

Because patent data is limited, prior research has suggested that additional information sources, like scientific literature and citations connecting patents to academic works, should be included [7, 11]. Citations to patents may serve as a gauge for the worth of innovation, according to these studies [47]. As a common tool for researching innovation trends and technological advancements, data on patents and cited academic publications are still utilized [48].

2.2 Patent as a gauge for the development of IoT data analytics technologies

Table 1 lists the few studies that have conducted patent analysis for IoT data analytics. The authors of one study [31] look at trends in popular IoT data analytics technology domains between 2014 and 2022. They find that there is a weak collaborative publishing network in their network analysis, and that compared to other fields, the field of IoT data analytics is relatively well-researched. The authors examined IoT data analytics patents in U.S between 1999 and 2020 in a different study. According to their analysis, U.S saw a rise in the issuance of IoT data analytics patents after 2005, with universities and businesses constituting the majority of patent applicants [30]. An additional study looked at IoT data analytics patents in Europe from 1989 to 2013. This study illustrates the dependence of patents on each other and have a strong relationship with the subtechnologies of IoT data analytics. Image, layout, and object are the top-level keywords, according to this study [32]. Research conducted by [33] indicates that there is a restricted co-occurrence among top institutions that specialize in IoT data analytics. The primary subjects covered by IoT data analytics include social media, cloud computing, business analytics, customer experience, healthcare, and web services.

Table 1. Few studies that have conducted patent analysis for IoT data analytics

Sl. No	Granted Patent Name	Inventors	CPC Classifications	IPC Classifications	Conclusion
1	“Method and system for analyzing internet of things (IoT) data in real-time and providing predictions”	“Bhattacharyya Sandipan, Ranganathan Deepalakshmi”	H04L67/12 G06N20/00 G06N7/023	G06N7/02 H04L67/12	The patent outlines a system and process for evaluating real-time Internet of Things data and forecasting future occurrences. Machine learning algorithms are used to create a predictive model, which is then adjusted based on how closely actual events differ from predictions.
2	“Automatic finding and sharing of IoT connected devices”	“Dawson Christopher J, Dow Eli M, Hamilton Ii Rick A, Li Jenny S”	H04L41/16 H04L41/5003 H04L41/5096 H04L67/303 H04L41/0897 H04L41/0893 H04L67/12 H04L67/141	H04L12/26 H04L12/24 H04L29/08	The text presents methods, computer program products, and systems for generating data profiles representing IoT devices and grouping them based on analytics and machine learning, with a mapping to virtual servers.
3	“Intelligent lifecycle management of analytic functions for an IoT intelligent edge with a hypergraph-based approach”	“Mopur Satish Kumar , Mukherjee Saikat , Vijayan Gunalan Perumal , Balachandriah Sridhar , Agrawal Ashutosh , Shastry Krishnaprasad Lingadahalli , Battas Gregory S”	H04L67/12 H04L67/02 H04L41/0816 H04L41/5045 H04L41/16 G06N20/00 H04L67/125 H04L43/045 H04L41/22 H04L43/091	G06F15/173 G06N20/00 H04L41/0816 H04L41/16 H04L41/22 H04L43/045 H04L43/091 H04L67/125	The text discusses a framework for managing analytic functions in an Internet of Things intelligent edge, allowing for seamless creation, deployment, evaluation, and refinement of these functions. The framework utilizes a hypergraph-based model and a microservices architecture with containerized microservices for machine learned infrastructure and models
4	“Aggregation of contextual data and internet of things (IoT) device data”	“Jain Saral , Dandekar Chetan Manohar”	G06Q30/0631 G06F16/211 H04L67/12 H04L63/1425 H04L67/306 G06F16/258 G06F16/284 G06F16/2455	H04L67/12 G06F16/21 G06F16/2455 G06F16/25 G06F16/28 G06Q30/06 H04L67/306	The text describes a technology for processing IoT device data by identifying and merging contextual data with the device data in a relational database, allowing for efficient reading and organization of the data.

3. Materials and methods

In order to measure the effectiveness of IoT data analytics invention activities, to identify the essential dynamics that characterize the patterns of innovation development hidden within Unstructured texts from scientific and patent literature, and to assess the strength of interactions between various agents within social networks. In this study, we have integrated social network analysis and bibliometric approaches. The IoT data analytics Inventiveness Network and the referenced academic works' communities and clusters, as well as the nodes, actors, and links and edges (the degree of interaction) between and among the nodes, were all identified and visualized using social network visualization techniques.

3.1 Data collection

Data has been collected from the Lens Open Source Platform. Lens describes the Lens database as a "global, open cyber infrastructure" for creative cartography on their website. The bulk of academic literature is accessible through links in the Lens record repository, which houses 95% of all patent documents worldwide. A number of patent data sources are included in the Lens: the DocDB bibliographic records from 1907 of the European Patent Office; USPTO applications from 2001; USPTO grants from 1976; USPTO assignments; 1980 European Patent Office (EP) grants; 1978 WIPO PCT applications; and Australian patent full text from IP Australia. Scholarly datasets are additionally integrated with PubMed, CrossRef, and Microsoft Academic.
The term "IoT data analytics using machine learning" was searched in title of the patent search. Dates, jurisdictions, and document types were all included. However, our classification was based on the IPC classification. Out of the three option full text, one document per family, and stemming, we decided on

stemming. The query language was also in English. November 15, 2023 was the completion date of the query. According to the search, there were 291 patent citations overall from patents that had cited 642 scholarly works. The software we employed for data analysis and visualization was as follows: The Lens platform is used by the Gephi 0.10.1 software, PatCite, Patent, and Scholarly. Lens serves as a platform for innovation cartography and an open global cyber infrastructure, providing access to worldwide patents and scientific knowledge for the general public. Its objective is to increase problem solving's accessibility, security, and inclusivity. Regarding our descriptive bibliometric examination, we employed the Lens platform, and for the social network analysis and visualization, we utilized the Gephi software.

This is an innovative approach. As far as we are aware, no study has been found that combines the following platforms for the scholarly works cited and patent analysis. After importing the CSV file extracted from the Lens platform, we checked the boxes corresponding to "creating links between applicants," "removing duplicates," and "removing self-loops in cases when an agent is connected to itself". The network of Lens Id and Applicants was an undirected graph with 438 nodes and 219 edges. We utilized the average weighted degree as our statistical method. How often an edge is passed between two nodes is displayed by the average weighted degree computation. The heavier the node, the stronger the connection is compared to one with a low weight [49]. The average weighted degree computes the average number of edges connected to the node, whereas the average degree computes the average weight of the edges connected to the node. We performed the average degree calculation on the network overview. At 0.934 on the weighted average, the average degree score was equal to 0.003. A network's degree of connectivity increases with its distance from 1 [50]. Considering their range of weighted degrees, we next filtered the network. The third layout that we selected was the circular layout (Fig. 1). In this paper's results section, the map's final version is explained in further detail.

To examine and display the network of applicants and jurisdiction, we used the same process. The network has an undirected graph type with 14 nodes and 7 edges. With respect to the applicant and inventor network, the average degree and weighted degree were both 1, indicating a highly connected network. Due to the network's high density, a predetermined filtering range between 57.94 and 347 in order to produce a clear representation of the network (Fig. 2).

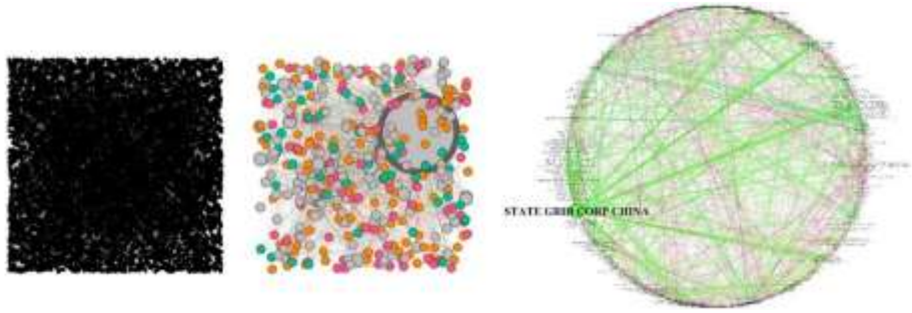

Fig. 1 shows the network of inventors and applicants in three different visualizations, from left to right: the first network is the initial visualization without any filtering; the second network is the network after applying steps 1 and 2; and the third network is the network after applying force atlas layout.

In order to highlight their networks of Lens Id and Applicants, we then limited the jurisdictions to the following: Japan, the US, the EU, the US, the WIPO, Canada, the UK, Germany, France, and the Republic of Korea. Jurisdictions where there aren't many IoT data analytics patent activities were also disregarded. For the network analysis and visualization, we used the same process.

Additionally, we examined and represented the scientific community's social networks publications that the patents cited. Our method of using modularity to find groupings for the co-occurrence network of keywords was. 1.0 is the resolution that is set. It had 0.213 modularity, and there were eight communities. Nodes with higher interconnectivity than the remainder of the network are sought after by modularity [51]. We employed the identical procedure for the networks of co-authors and study fields.

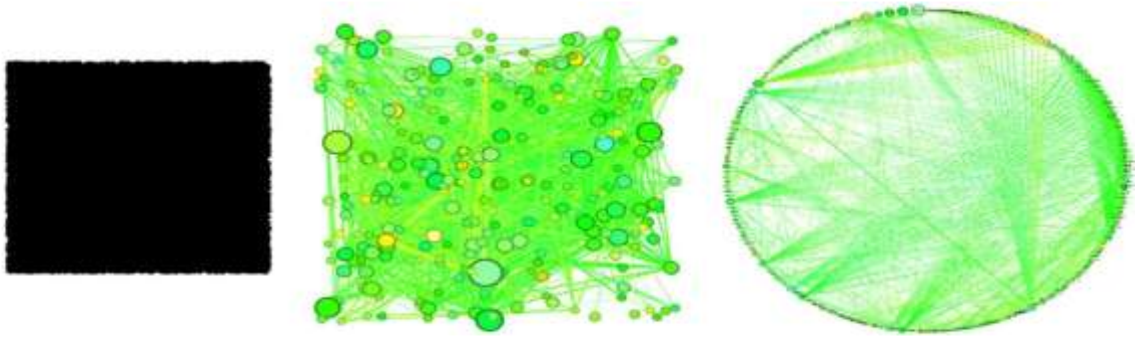

Fig. 2 shows the network of applicants and jurisdiction in three different visualizations, From left to right, the first network represents the initial, unfiltered visualization; the second, the network following the application of steps 1 and 2; and the third, the network following the application of the force atlas layout.

4. Results

4.1 Descriptive bibliometric analysis

13,432 academic scientific publications that were cited in 24,931 patents were examined. The Lens Platform served as the source of these documents.

Regarding the historical development of productivity in science and invention, as depicted in Fig. 3, how productive inventions are related to IoT data analytics saw a significant spike in 2022 with the granting of patents in 2000, and then continued to rise steadily until 2022. In 2020, there were 1067 patents granted, a sharp increase from the 1700 patents in 2021. 2019 saw 567 patents, continuing the same upward trend. No applications were submitted prior to 2014. There were eighteen applications submitted in 2014. But with only 238 applications indexed in 2018, the number of patents increased marginally in 2018. Out of all the people who applied for patents, 238 of them were approved, and 1153 of them were restricted.

In reference to academic research on IoT data analytics, as illustrated in Figure 3. With 74 patents in 2019, the interaction between patents and academic works increased significantly. After that, the quantity of works that are cited steadily decreased, reaching 66 in 2017. However, considering that only 238 saw the indexing of applications in 2018 and the quantity of patents in 2020 increases dramatically. The patent with the most recent priority information was provided in 1997 and published in 2000. A limited patent bearing the IPC classification G03G15/00 was the first IoT data analytics data patent. G is an abbreviation for physics, G06 is an abbreviation for computing, and G064 is an abbreviation for digital electrical data processing. This innovation provided a method for gathering and handling IoT analytics files.

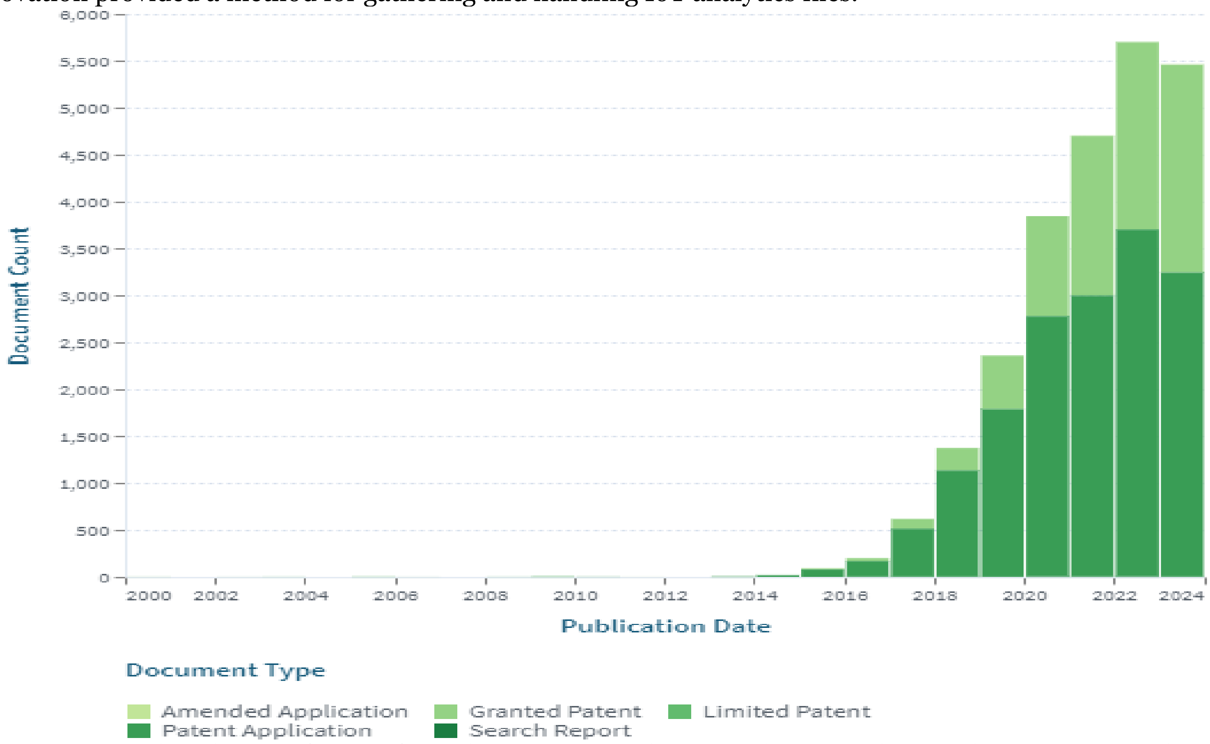

Fig. 3 Temporal evolution of scientific and invention productivity about IoT data analytics patent applicants per year

As demonstrated in Fig. 4, Cella Charles Howard has the most patents with 699 inventions, earning him the title of inventor with the most inventions. This analysis aids in determining the greatest inventors as well as the subject matter of their inventions. The majority of his works are classified as physics and machine learning, or G06N20/00, according to the IPC classification, as shown in Fig. 5. For the majority of his inventions, Strong Force IoT Portfolio 2016 LLC was the applicant. Strong Force IoT Portfolio 2016 LLC is one of the main applicants for his works among the others. His applicants are all US-based businesses.

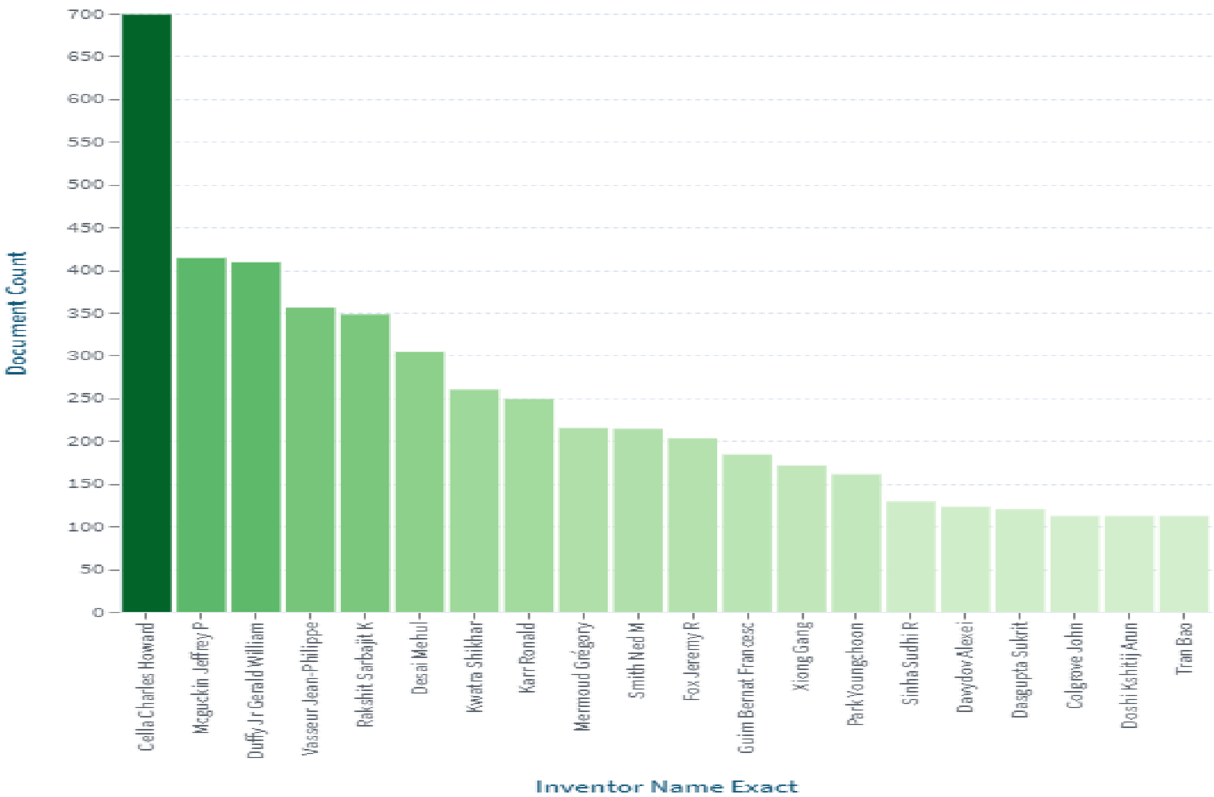

Fig 4. The names of the leading inventors and the quantity of patents they have been awarded

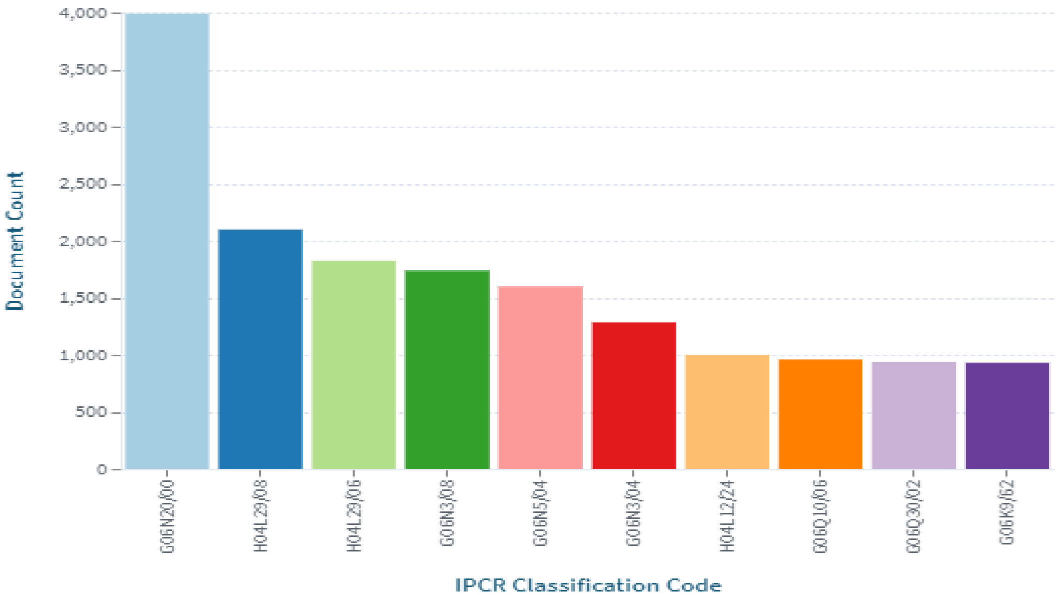

Fig 5. Cella Charles Howard's IPCR classification numbers

The second-highest patent-holding inventor is Jeffrey P. Mcguckin. His creations account for half of the first inventor's total of 414 inventions. The majority of his patents fall under the G06N20/00 IPC classification for physics and machine learning. Among the ten candidates vying for his services is Strong Force IoT Portfolio 2016 LLC. He does not claim any of his inventions as his own.

The majority of Duffy Jr Gerald William creations with 409 inventions, ranks third among inventors with the most. His inventions fall into the physics and machine learning IPC category, G06N20/00. The majority of

Vasseur Jean-Philippe creations, who ranks fourth among inventors with 356 inventions, fall under the G05B19/418 Physics Total factory control category. Duffy and Vasseur major patent applicant is Strong Force IoT Portfolio 2016 LLC. Rakshit Sarbajit K is the fifth inventor with the most patents. His principal contributions are classified as physics and machine learning under IPC code G06N20/00. The applicants for Kyndryl INC. and IBM are for Rakshit Sarbajit K.The United States of America has filed more patent applications for iot analytics data than any other nation, according to our investigation into each applicant's patent counts. with organizations such as IBM United States of America achieving the top spot.
IBM, Intel Corp., Cisco Tech Inc., Splunk Inc., Pure Storage Inc., Sas Inst Inc., Strong Force IoT Portfolio 2016 LLC, AT&T Inc., Apple Inc., Microsoft Technology Licensing Llc., Verizon Patent & Licensing Samsung Electronics Co Ltd Johnson Control Inc., and Accenture Global Solutions Ltd. are the main US applicants for IoT data analytics patents.
The United States of America is in the lead and in first place according to the examination of the countries where the most patent applications are submitted (Fig. 6), having filed 20,695 IoT data analytics patent applications in total (i.e., 86% of worldwide patent filings). WIPO applications ranked second with 2793 (equivalent to 8% of all applications worldwide), while Republic of European countries applications came in third place with 889 (equivalent to 4% of all applications worldwide). China, with five filings (or 1% of all patent applications worldwide), and Australia, with four filings (or 0.75% of all applications), abruptly top the list. Korea has two applications on the list, and Russia has one (or 0.25 percent of the applications worldwide).

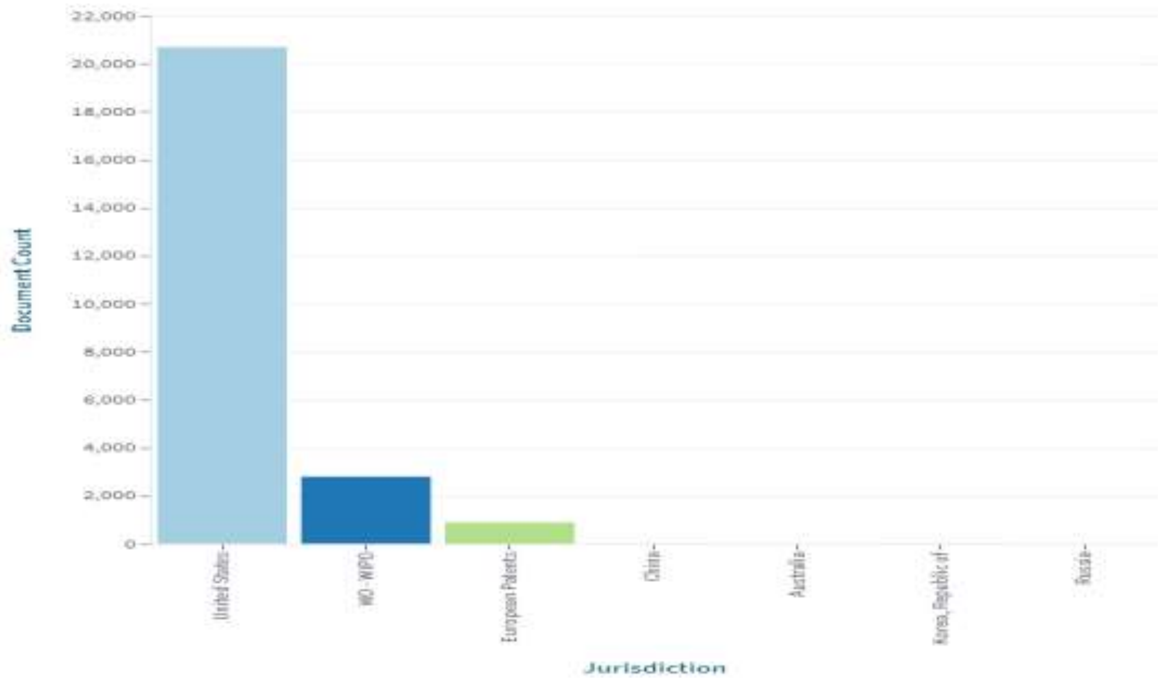

Fig. 6 A chart showing the patent applications filed in different countries

The term "International Patent Classification" (IPC) refers to a hierarchical classification system that is mainly used to search and classify patent documents (granted patent specifications, utility models, and application materials) based on the technical fields to which they belong. The majority of IPC categorization is used for filing patent applications. of G06N20/00, according to this analysis's analysis of patent classification (Fig. 7). G stands for physics in this classification, and G06 for computing, counting, or calculation. The term machine learning is G06N20/00. Physics architecture, or interconnection topology, is denoted by G06N3/04, and physics learning methods are denoted by G06N3/08. The term "physics inference" or "reasoning models" is G06N5/04. Project, human, and workflow management in physics are all referred to in G06Q10/06. The term "physics marketing price estimation or determination fund raising" (G06Q30/02) describes this. The patent family was categorized primarily into G, H, and Y. Here, physics is denoted by G, electricity by H, and emerging cross-sectional technologies by Y.

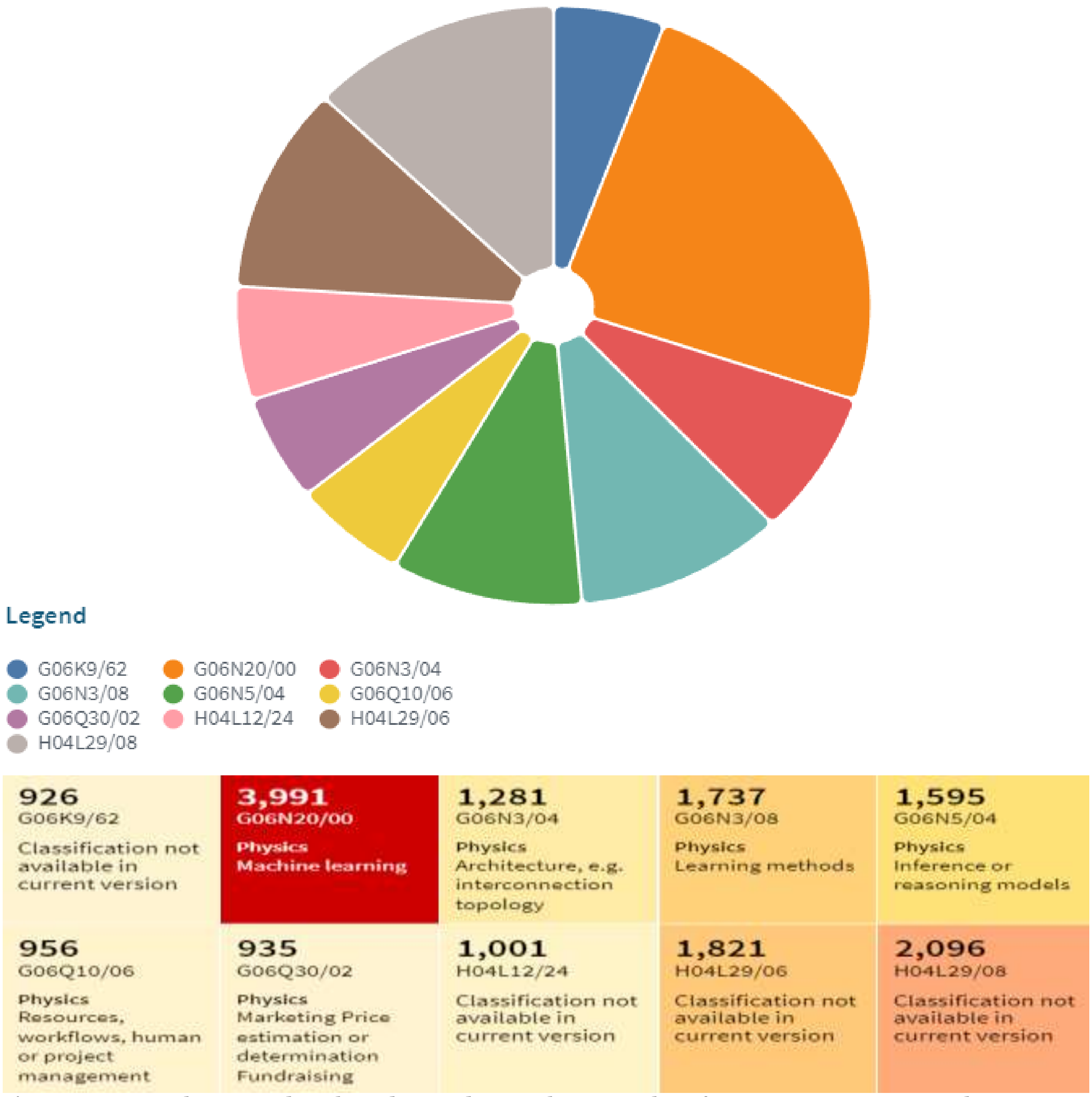

Fig. 7 Patent applications distributed according to their IPC classification. Most patent applications are classified as physics-related, followed by the category of electricity, as this figure illustrates. A typical amount of patents fall into the category of developing technology that crosses sectors.

4.2 Citation linkage analysis of patents to scholarly works

To begin, In this section, we provide data on scientific work citations based on worldwide patents. Next, we examine the regions that have the highest percentage of receiving IoT data analytics patent applications the Europe Patent Office, WIPO, China, and the United States.

The patent with the highest Cited count, 1,137, is "Systems, Methods, and Devices for an Enterprise Internet-of-Things Application Development Platform." The inventors are David Tchankotadze, Scott Kurinskas, James Coker, Behzadi Houman, Thomas M. Siebel, and Abbo Edward Y. On October 27, 2020, the patent was awarded based on an application submitted by C3 Inc.

"System and Method for Extremely Efficient Image and Pattern Recognition and Artificial Intelligence Platform" was the second-most cited patent, with 945 citations. The inventors are Tadayon Saied, Tadayon Bijan, and Zadeh Lotfi A. Z Advanced Computing Inc. filed the application, which resulted in the patent being granted on July 19, 2018. Fig.8 represents top cited patents with publication date.

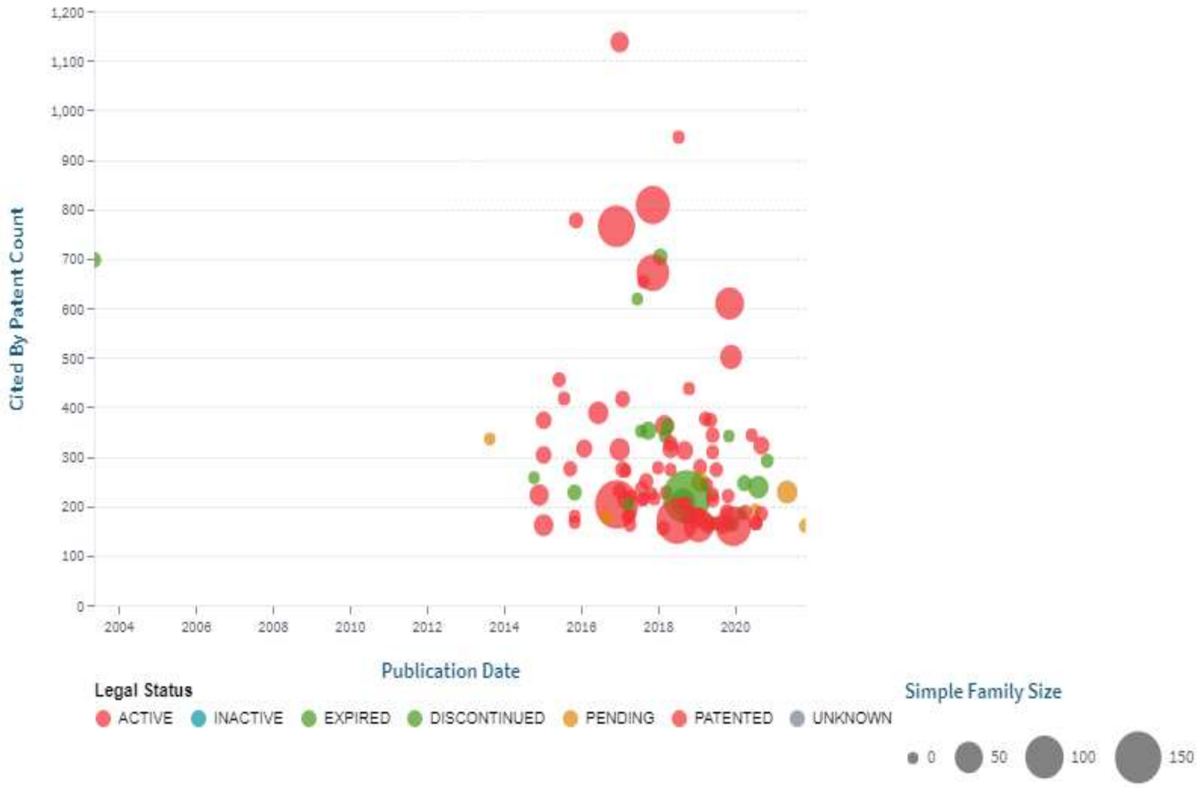

Fig.8 represents top cited patents with publication date

4.3 IoT data analytics social network analysis of invention activities

The network of international Lens Id and Applicants was examined in this section of the paper. We have also made this network visually appealing for significant jurisdictions. The networks of authors, fields of study, and keywords that appear in the referenced scientific publications were all visualized in the following step.

According to the weighted agent's degree, Applicants' and Lens Id's network is displayed, as was described in the Methodology section. Following the filtering, Figure 9 shows a Network of Applicants and Lens Id with 438 nodes and 219 edges. The agents with a weak connection and low weighted degree are represented by the blue lines, while those with a stronger connection and higher weighted degree are represented by the green lines. A weak connection between the nodes within the network is indicated by the analysis, which reveals that the weighted degree of 6020 (78.88%) elements was 0. A significant correlation in the applicant's relationship with the other network applicants is indicated by the weighted degree of 446 for one element—the US.

Similarly, when the network of “Applicants” and “Cited by patent count” is applied to Gephi shows that there are 299 nodes and 1000 edges. Statistical analysis parameters related to network overview are defined as follows. An edge's average number of connections to a node is referred to as its average degree, which is 1.666 after run. The average of the weights of the edges that connect a node to its average weighted degree, which is 3.334 after run. The graph's density indicates how near completion the graph is, which is 0.011 after run. The longest and shortest path between nodes in a graph is called the network diameter, which is 9 after run. Statistical analysis parameters related to community detection are defined as follows. Network community represents densely connected applicants. The modularity of the network graph determines how much of it is divided into clusters. Dense connections within a cluster and sparse connections to nodes outside of it are indicative of high modularity. Gephi employs the modularity approach of Louvain, which is 0.273 after run. According to the analysis, U.S. companies account for most of the candidates with the highest weighted degree. The total of the in degree and out degree is the degree. Out degree indicates the number of times a node points to itself. The number of times other nodes point to a specific node is indicated by its in degree. Fig.10 shows graph for applicants and cited patent counts, degree, out degree and in degree.

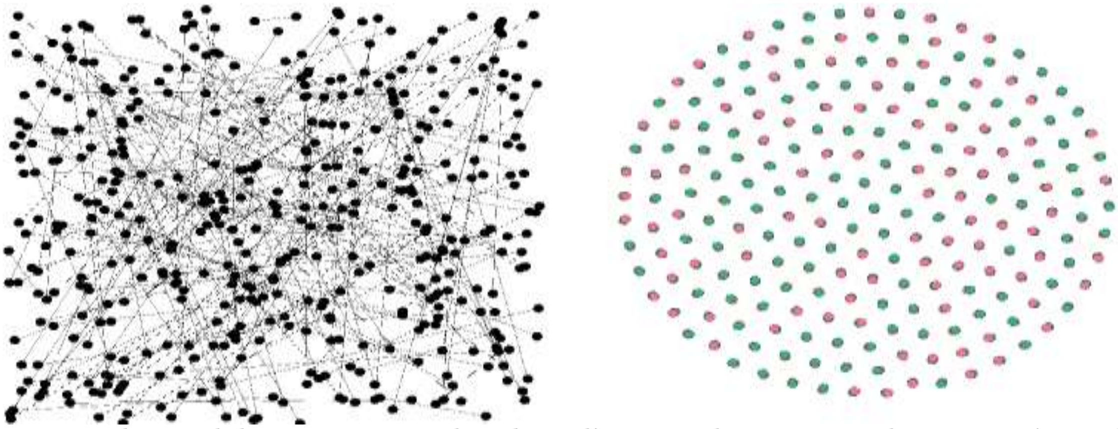

Fig.9. Network Graph between Lens Id and Applicants, when Force Atlas Layout is applied

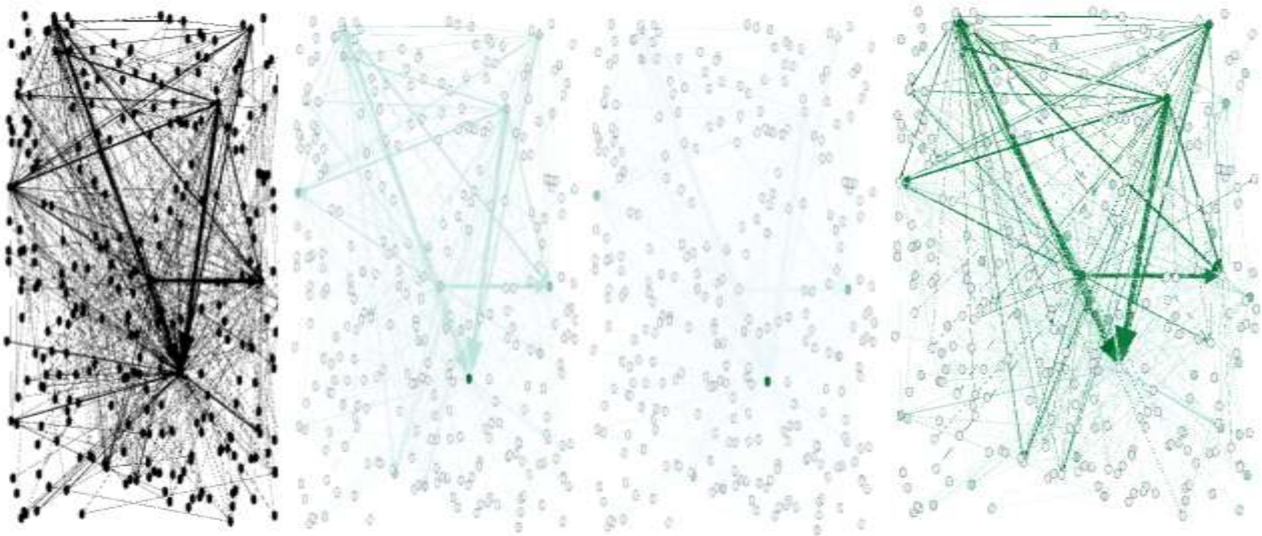

Fig.10. Network Graph between Applicants and Cited Patent counts, Degree, In degree Out degree applied

5. Discussion and conclusion

This study combined bibliometric and social network analysis techniques to ascertain the trends of development in IoT data analytics patenting activity as well as the relationship over time between patents and the cited scientific literature. It also looked at how agents—such as applicants, cited authors, and inventors—interacted with one another within the social networks. To the best of our knowledge, this study is the first academic work that compares the evolution of IoT data analytics and innovation globally, the connection between science and patents, and the level of the connectivity between agents in social networks.

This analysis shows that when it comes to IoT data analytics patent applications filed worldwide, the US is in the lead. Applications for WO-WIPO lagged significantly. Only six among the top ten applicants for patents on IoT data analytics are from American companies and academic institutions occupy the other eight spots. A U.S. company tops the list with more patent applications than twice that of IBM, which ranks second out of ten. On the other hand, as of January 2019, Just 5% of all patent applications submitted are handled by the US were patented, compared to 28% of patents filed in the US.

This analysis also shows that, in terms of the quantity of IoT data analytics patent applications filed, American inventors continue to lead the world; specifically, they rank ranked first, second, and fifth among inventions related to IoT data analytics. Consequently, this analysis shows how US companies are the ones who file the majority of requests for patents and receive the majority of patent awards. The majority of inventors, according to this analysis, are employed by big companies and do not file patent applications for their creations.

The United States leads the world in the number of filed patent applications, with 20,900 (or 78% of all applications filed globally) filed under its jurisdiction. Second, WO-WIPO is home to 2806 patent applications, or 8 percent of all submissions filed globally.

According to this analysis, the IPC classification G06N20/00 for Machine learning and physics is where most patent applications are filed. Compared to the 2009 the earliest priority patent in date, which was filed in 2009, the study indicates that the greatest number of patent applications pertaining to IoT data analytics were filed in 2023 (2,314).

There is a low correlation between citations of scientific works and inventions; only 2.2% of patent applications worldwide have cited scientific works. In contrast In comparison to other regions, the US and Europe have the most powerful connections to academic literature in their patent justifications (the US has 15% and the Europe jurisdiction has 14% of citations to scholarly works, respectively). In sharp contrast to the amount of cited academic works, for patent applications, China cited fewer than 1%. In addition, 2022 recorded the highest quantity of citations. The number of IoT data analytics-related patent applications peaked in 2022, while the number of academic publications cited fell by half. Thus, inventions and scholarly works appear to be strongly correlated prior to 2019 and to be increasing in 2020. Remarkably few citations to academic publications are included in China, despite the fact that citing prior art—including scholarly works—is required in all jurisdictions. This is due to the practices of the patent office and the lax enforcement of information non-disclosure laws.

In comparison the top-ranked country in terms of patents, the United States applications, Intel, as the second applicant with the most applicants, has a weak connection in the global network. Additionally, the application network shows that IBM has very strong links with the other applicants. The bulk US applicants and inventors possess greater networks than their American counterparts. counterparts, whereas applicants in the European and WIPO jurisdictions have no connections at all within the network, suggests this analysis. Still, most applicants are connected to each other to a similar extent and are not very different from each other throughout the US, UK, France, WIPO, and Canada network authorities. Although most applicants are unemployed and do not know anyone in the network, some, like Microsoft and IBM, have created small communities within it. Unlike the co-applicant network in these specific jurisdictions, The co-inventors' network is robust. ties within its applicants. The co-occurrence of keywords indicates even more that the majority of keywords are associated with computer science-related fields. Authors who are experts in areas such as radiology, molecular imaging, and cancer are distinguished by stronger links within the coauthor network. Among the scientific fields with the most robust networks are computer science, engineering, and medicine. This study shows that one of the most promising uses of IoT data analytics innovations is in the treatment of cancer. making the case that companies studying other complex illnesses can also benefit from IoT data analytics advancements and focusing their R&D efforts on creating new IoT data analytics tools.

5.1 Limitations and future research directions

It is important to recognize the limitations of this study. Originally, the study's sole data sources were scholarly works referenced in patents and patents themselves. We did not have access to the scholarly articles that referenced patents. As such, quantifying the connection between cited academic works and patents became impossible after 2015. Third, there are many applications and a great deal of complexity in the field of IoT data analytics. Rather than focusing on a specific IoT data analytics software or hardware layer, we measured the overall innovation evolution of the market. The fourth drawback was that instead of evaluating each jurisdiction's patenting activity in detail, we focused on making a worldwide comparison. Given the following constraints, future studies may focus only on specific IoT data analytics landscape layers, companies, or legal jurisdictions. It might also be possible to conduct further research on the subject of why US patent applications for IoT data analytics are the highest.

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