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Exploring the Landscape of AI-SDN: A Comprehensive Bibliometric Analysis and Future Perspectives

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Abstract: The rising influence of artificial intelligence (AI) enables widespread adoption of the technology in every aspect of computing, including Software-Defined Networking (SDN). Technological adoption leads to the convergence of AI and SDN, producing solutions that overcome limitations present in traditional networking architecture. Although numerous review articles discuss the convergence of these technologies, there is a lack of bibliometric trace in this field, which is important for identifying trends, new niches, and future directions. Therefore, this study aims to fill the gap by presenting a thorough bibliometric analysis of AI-related SDN studies, referred to as AI-SDN. The study begins by identifying 474 unique documents in the Web of Science (WoS) database published from 2009 until recently. The study uses bibliometric analysis to identify the general information, countries, authorship, and content of the selected articles, thereby providing insights into the geographical and institutional landscape shaping AI-SDN research. The findings provide a robust roadmap for further investigation in this field, including the background and taxonomy of the AI-SDN field. Finally, the article discusses several challenges and the future of AI-SDN in academic research.

Keywords: artificial intelligence; Software-Defined Networking; bibliometrics; machine learning; data visualization

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1. Introduction

Artificial intelligence (AI) technology is a fast-growing field due to its presence in every corner of the world's industries. From chatbots and image generators to mobile applications, the broad implementation throughout many fields made AI inevitable for people. A study of AI market size predicted that it would grow from $100 billion to nearly two trillion US dollars, making a twentyfold increase [1]. Additionally, the release of ChatGPT 3.0 in 2022 amplified attention throughout the industry and academia, as the tool enables everyone with Internet access to use AI effortlessly. Meanwhile, from a computer science research perspective, the computer networking domain is one of the fields that enjoys the positive impact of AI growth.

In computer networking, the Software-Defined Networking (SDN) domain has grown tremendously after more than a decade of its inception. The term was coined in 2009 to introduce a new networking paradigm enabling dynamic network management by splitting control and forwarding network functions [2]. SDN enables centralized control through programmable networks, coupled with AI technologies, provides automation, and reduces human intervention [3,4]. The combination of the two technologies solves the limitations present in traditional network architecture, such as resource provisioning, scalability, and physical infrastructure, which justifies the enormous growth in AI-based SDN solutions [5]. Therefore, we believe it is important to analyze the research area in AI-related SDN studies to increase understanding and provide a clear vision of the topic, current trends, and future possibilities.

Currently, many published articles regarding the advancements in AI-based SDN techniques can be found via publication indexes such as the Web of Science (WoS) and Scopus. Among these publications, review articles provide readers with an overview of the field by summarizing the current state of knowledge. The authors of a review article achieved the goal by synthesizing or analyzing the existing works and identifying the advantages, limitations, and future research directions. These articles may vary in their scopes; for example, [6] reviewed the AI-related technologies in SDN for industrial Internet-of-Things (IoT) and discussed the security challenges that come with the technology. [7] reviewed the current research efforts in AI-SDN, focusing on machine learning, meta-heuristics, and fuzzy inference systems. Despite the growing body of literature on AI in SDN, there is a noticeable gap in comprehensive bibliometric analyses that map out the evolution, key contributors, and emerging trends in the domain. The existing literature, although informative, does not fully encapsulate the most recent advancements and trends in AI-based SDN. Motivated by the gap, our study provides a comprehensive bibliometric analysis that offers a holistic view of the AI-SDN research landscape. Additionally, this study contributes to the knowledge of the current state of AI-SDN research, whereby insights aid in identifying key areas for potential collaboration, niche topics, and informing policymaking.

This study aims to present a thorough bibliometric analysis, including network collaboration of AI-related SDN research practices, from its induction in 2009 until recently. The analysis identifies the most influential literature, determines the discipline area within the subject, provides insights into the trend, and highlights the future directions of AI-based techniques in SDN. The methodology involves collecting data from the WoS Core Collection database, using the topic search term "artificial intelligence", and applying the logical AND function with the keyword "software defined networking" to extract the documents related to the field. The resulting dataset comprises 474 items in the literature, specifically in the AI-SDN field. The analysis of the dataset provides four perspectives: general description, countries, authors, and content. The findings highlight the results from these perspectives using several variables, including authors, sources, contents, citations, and origins. The network perspective illustrates the relationship of each document or author, graphically showcasing the type of relationship with one another. An extensive content analysis using the mobile communications sub-domain in AI-SDN also provides an example of dynamics between authors, countries, and their sub-topics. Finally, this paper discusses the taxonomy of AI-based studies in SDN and explains the current methods thus far.

The remainder of this paper is as follows: Section 2 begins with an explanation of bibliometric analysis and related work in the field. Section 3 divulges the methodology used in this research, from identifying the correct search keyword to data collection, analysis tools, and the resulting outcome. Section 4 highlighted the findings of the bibliometric analysis, discussing each metric selected in the study. Section 5 provides the background and elaborates on the taxonomy of AI-SDN research. Section 6 discusses the challenges and provides future research directions. Finally, Section 7 concludes the paper.

2. Related Work

Literature reviews are crucial to academic research because they gather knowledge of the existing field and identify potential limitations. There are several methodologies to conduct a thorough literature review, such as systematic literature review (SLR) and bibliometric analysis (BA), each with specific methods. In the literature, SLRs and review articles are popular among researchers as a knowledge source for a specific domain. However, with the rapid increase of publication volumes in the modern age, it becomes increasingly difficult to keep track of the developments in a field of study [8]. This problem causes a struggle for researchers to identify a relevant topic to focus on and requires new techniques to uncover research articles, including AI-based SDN studies. Bibliometric analysis is one solution that solves the problem of analyzing abundant literature documents.

Currently, there are many SLR and review documents in the paradigm of AI-SDN. These systematic reviews discussed a variety of topics, including SDN architecture [9], security [10,11], and SDN-IoT [6]. These articles comprehensively elaborate on the field and critically analyze the methodologies, techniques, advantages, and disadvantages of each domain. However, these reviews only cover the domain according to a specific period, for example, five years. The review style lacks the ability to analyze the literature over a longer timeframe to present the growth of a specific topic from its inception point. In order to analyze this growth, another form of literature analysis, bibliometric analysis, is used to achieve the objective.

Bibliometric techniques analyze, discover, and visualize the structure of scientific fields [12]. It describes the growth of a domain by evaluating its performance using several metrics, such as citation count, impact factor, authors, publishers, and keywords. Certain studies have employed the bibliometric technique in the SDN domain to conduct research. For example, ref. [13] conducted an analysis using the Scopus database on the topic of SDN security, while [14] studied the metrics for the prospective Information and Communications Technology (ICT) fields using bibliometric techniques. The results from both studies uncover the growth of specific sub-fields in the domain, allowing researchers to focus on trending topics. However, there is still a lack of studies using bibliometric techniques in SDN to uncover the current trend, growth, and challenges in the domain, specifically in AI-related SDN, which motivates our investigation. Table 1 summarizes the existing work carried out in the domain according to its article type and research scope.

Table 1. Summary of related work in the AI-SDN domain.

Reference	Article Type	Scope	Description
[9]	SLR	SDN data plane	A systematic review of the failure recovery solutions in the SDN data plane using traditional and AI-based solutions.
[10]	SLR	SDN security using AI	A systematic review of SDN DDoS attacks and detection approaches using ML, DL, and hybrid techniques.
[11]	SLR	SDN security using AI	A systematic review of ML/DL approaches for SDN DDoS attack detection.
[6]	Review	AI-SDN in industrial IoT	A review of the security and functionality of AI-enabled industrial IoT in three functional layers.
[13]	Bibliometric analysis	SDN security	A bibliometric analysis of the current SDN trends while discussing available challenges and solutions.
[7]	Review	AI-SDN	An overview of recent research efforts to incorporate AI in SDN using three sub-fields: ML, meta-heuristics, and fuzzy systems.
[14]	Bibliometric analysis	General ICT domains	An analysis of major ICT domains using information distance metrics and semantic networks.
This study	Bibliometric analysis	AI in SDN	A bibliometric analysis of AI-related SDN research articles and discussion of the current research landscape and challenges

3. Methodology

This paper employs a specific methodology to conduct the study. The methodology consists of four phases: identifying search keywords, collecting data, conducting analysis, and discussing the findings. Figure 1 illustrates the methodology phases used to conduct this study.

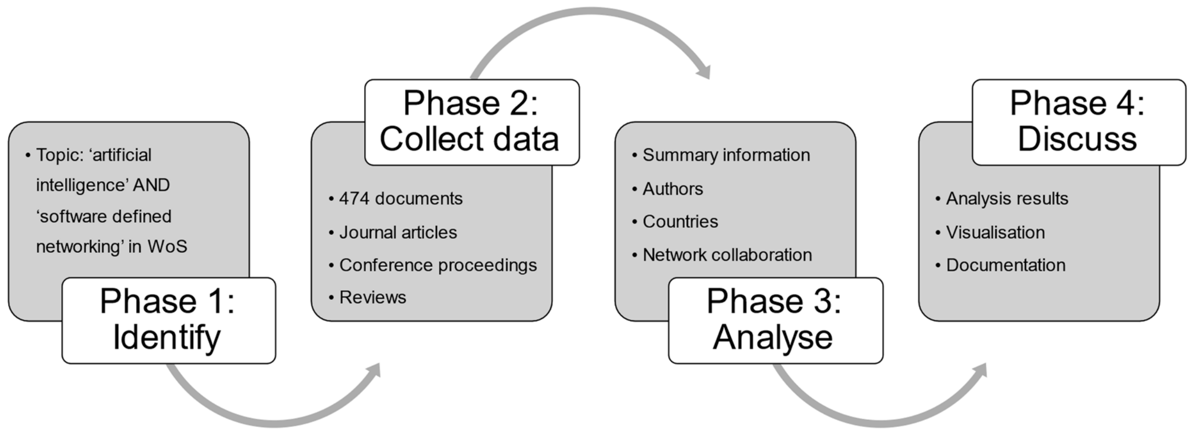


Figure 1. Methodology phases of the study.

Firstly, we determine the main keywords to identify the subject of the analysis. Based on the research gap from the previous section, we chose the topic keywords "artificial intelligence" and "software defined networking" as the main keywords to conduct our search according to the scope of the paper. Then, to apply the search, we chose a specific database, the WoS Core Collection, which provides bibliometric data for literature searches. The database contains important features comprising all article types, indexes, authors, and bibliometric references [15]. Additionally, it is a comprehensive database with a large collection of high-impact publications compared to others, such as Scopus and Google Scholar [16]. These factors justify our choice in selecting the right keyword and database to establish the scope of this study.

The second phase involves the process of data collection based on the selected keywords and database. Using the search query in the WoS database, we obtained 474 literature documents published from 2009 until 2023, from the early introduction of SDN to the most recent adaptation of AI into SDN. The query uses the Boolean operator 'AND' to restrict the query specifically to topics related to AI-SDN only, which resulted in a dataset of literature documents being collected. These documents were carefully checked to omit any duplication or unrelated topics using well-defined inclusion and exclusion criteria. The inclusion criteria for this study focused on articles that explicitly discussed the convergence of AI and SDN or those that presented significant findings, methodologies, or reviews in the field of AI-SDN. The exclusion criteria omit articles that, although possibly mentioning AI and SDN, did not contribute directly to the core focus of AI-SDN convergence, such as papers where these terms appeared tangentially or in unrelated contexts. This process was essential to maintaining the relevance and quality of the analysis, ensuring that the final selection of articles provided a comprehensive and accurate representation of the current state of AI-SDN research.

The third phase is to analyze the collected dataset of documents. During this phase, we used several software tools to conduct the analysis. Multiple tools are available for conducting bibliometric analysis, for example, BibExcel, Gephi, Pajek, HistCite, and the R bibliometrix package ver. 4.1. However, certain tools have limitations that restrict the research outcomes. The BibExcel tool is limited in operational complexity and requires experience to conduct a simple analysis. Meanwhile, Gephi, Pajek, and HistCite have constraints regarding the lack of capabilities for data preparation across different types of datasets [16]. Therefore, we picked the free and open-source programming language R (version 4.3.2), supported by the 'bibliometrix' package ver. 4.1 [17]. The tool offers dynamic and efficient analysis as it is programmable and customized to users' needs. It also provides a graphical user interface (GUI) to ease its use and is suitable for adaptation in multiple research fields.

Finally, the outcome of this research article discusses the results and findings from the analysis. It summarizes the field's trends, importance, limitations, and future directions to guide researchers exploring the domain.

4. Results

This section is divided into four subheadings: descriptive, countries, authorship, and content analysis. It provides a concise overview of the data analysis results and discusses key observation points for each metric.

4.1. Descriptive Analysis

The descriptive analysis section offers a snapshot of the gathered literature, presenting essential statistics that paint a comprehensive picture of AI in the SDN research landscape. Table 2 encapsulates the primary attributes of the 474 documents published between 2009 and 2023. These documents have been sourced from 312 distinct outlets, spanning a variety of journals, books, and conferences. Regarding content analysis, there were 1887 authors' keywords and 631 Keywords Plus. The authors' keywords represent terms frequently appearing within the document, while Keywords Plus is derived from the most recurrent terms in the titles of literature references.

Table 2. Summary information of the dataset.

Description of the Dataset	Value
Timespan	2009:2023
Sources (journals, books, conferences, and others)	312
Documents	474
Average citations per document	14.04
References	21,940
Keywords Plus	631
Author's keywords	1887
Authors	1677
Authors of single-authored documents	21
Single-authored documents	23
Documents per author	0.282
Authors per document	3.54
Co-authors per document	4.17
International co-authorships (%)	35.65

A look into the authorship statistics reveals that the dataset encompasses 1677 authors. Twenty-one of these authors, or approximately 1.25%, have penned single-authored literature, making up about 23% of the documents. On average, each document has 3.54 co-authors, with an internationally affiliated co-authorship rate of 35%. Each document, on average, garnered 14.04 citations, suggesting a moderate impact. Cumulatively, the 474 documents cited 21,940 references.

Table 3 provides a deeper dive into the nature of the collected documents. Notably, articles constitute nearly 60% of the dataset, underscoring the robust academic contribution to AI in SDN. Conference papers make up almost 30% of the dataset. In contrast, categories like book chapters, books, reviews, and other types are either non-existent or minimally represented in the dataset.

Table 3. Types of literature items in the dataset.

Description of the Dataset	Value	% of Dataset
Article	282	59.5%
Proceedings paper	142	29.9%
Review	34	7.1%
Others (meetings, notes, and editorials)	16	3.3%

4.1.1. Subject Area

Subject area analysis provides a comprehensive view of the literature within the field of AI in SDN, detailing the specific areas of focus and exploration. This categorization, based on the well-established Web of Science Research Areas, enables researchers to gauge the depth and breadth of each domain based on their publication rates, offering insights into the state and direction of research. Table 4 presents these subject areas alongside their respective percentage representations in the dataset. With its significant prominence, AI in the SDN domain investigates the integration of machine learning and artificial intelligence techniques to optimize, secure, and innovate new networks.

Table 4. Analysis of literature items in the subject area.

Subject Area	Value	% of Dataset
Computer Science Information Systems	384	81.0%
Engineering	195	41.1%
Telecommunications	172	36.3%
Material Science Multidisciplinary	17	3.6%

The engineering aspect of this field might delve into the technical intricacies of implementing AI algorithms within SDN infrastructure to enhance performance, reduce latency, and predict potential SDN threats. The Computer Science and Information Systems domain would focus on the algorithmic challenges and solutions of integrating AI into SDN, ensuring efficient resolution and response times. Given its inherent nature, telecommunications would explore the impact of AI on SDN concerning network communication, data transmission, and overall internet connectivity. Lastly, while seemingly distant, the Materials Science area investigates hardware or physical components supporting the deployment of AI-enhanced SDN systems. While AI integration in SDN is considered a niche area, its multidisciplinary approach ensures a holistic and forward-thinking approach to future internet infrastructure and network security.

4.1.2. Annual Growth of Publications

The annual growth rate offers insights into the evolving interest in a particular research domain. From 2009 to 2023, the dataset reveals an annual growth rate of 22% in the AI-SDN field. As depicted in Figure 2, the research trajectory in this field has been upward. Notably, prior to 2015, the publication rate was relatively subdued, with fewer than 50 articles annually. However, post-2016, there was a marked surge in publications, culminating in a peak of 110 articles in 2022. Until August 2023, the number of articles was 65, suggesting sustained interest in the domain. This uptick underscores the escalating attention from academia and industry toward AI challenges and utilization in SDN.

Scrutinizing the growth shown in Figure 3, which portrays the cumulative growth of documents from the top seven sources, reveals intriguing patterns. Among these sources, "*IEEE ACCESS*" has demonstrated the most robust growth, with its publications seeing a significant rise from 2018 onwards, reaching 37 articles by 2023. Notably, "*Sensors*" and "*Applied Sciences-Basel*" began their contributions in 2020 and 2017, respectively, showing consistent growth. The "*Journal of Lightwave Technology*", despite its early presence in the dataset, has maintained a steady contribution, reaching six articles in 2023. These trends underscore the burgeoning interest and the diverse avenues of research in the domain from various reputed sources.

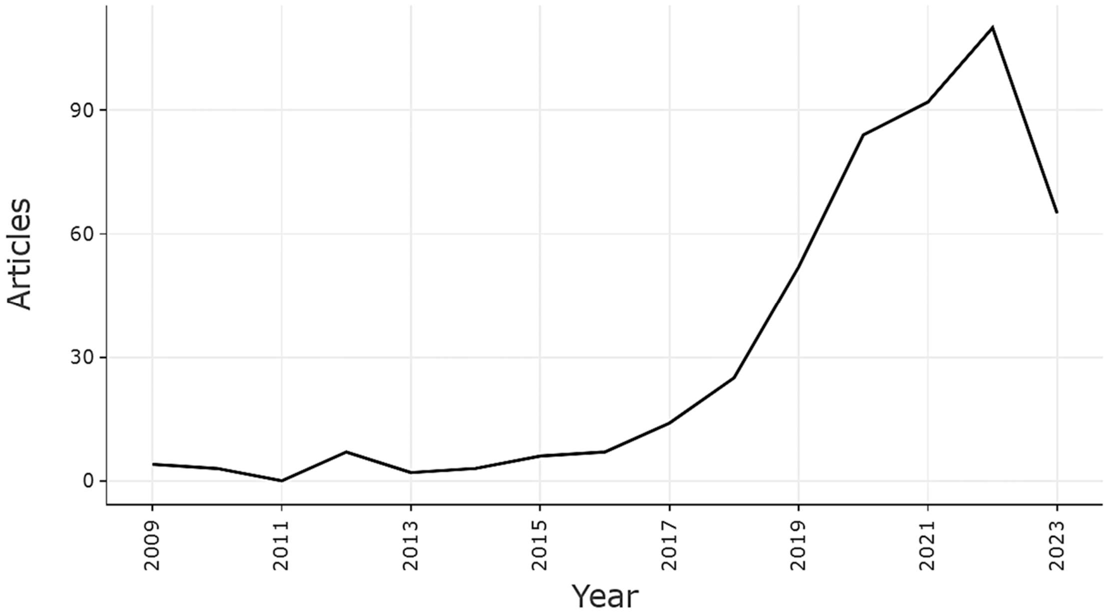


Figure 2. Yearly publication growth for the AI-SDN domain.

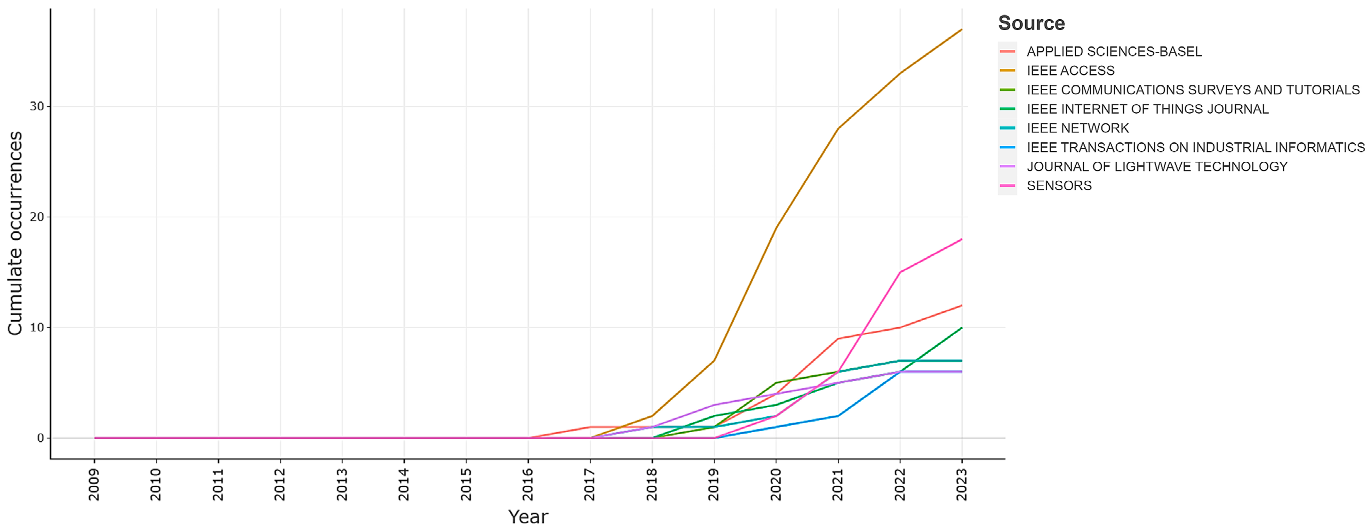


Figure 3. Cumulative growth based on document sources.

4.1.3. Top 15 Impacting Sources

The impact and productivity of scientific sources can be gauged through a combination of metrics. In the context of AI in SDN, the dataset comprises several sources, with a few standing out regarding their contributions and influence. Table 5 lists the top 15 scientific sources based on their h-index, g-index, number of publications (NP), total citations (TC), local citations (LC), and publication year started (PYS).

"*IEEE Access*" emerges as a dominant source, boasting the highest number of publications (37) and an impressive g-index of 31. It has also amassed a significant 984 citations since its inception in the field in 2018. Another notable source is "*IEEE Communications Surveys and Tutorials*", which has received a staggering 1385 citations despite having only seven publications. The "*IEEE Internet of Things Journal*" and "*Sensors*" have also made substantial contributions, with both sources starting their publications in the latter part of the decade and already making a significant impact.

Table 5. Analysis of the top 15 most impacting sources in the dataset.

Source	h-Index	g-Index	NP	TC	LC	PYS
IEEE Access	15	31	37	984	956	2018
IEEE Communications Surveys and Tutorials	6	7	7	1385	611	2019
IEEE Internet of Things Journal	6	10	10	167	435	2019
Sensors	6	11	18	140	6	2020
IEEE Network	5	7	7	97	258	2018
IEEE Transactions on Industrial Informatics	5	6	6	211	195	2020
Journal of Lightwave Technology	5	6	6	301	117	2018
Applied Sciences-Basel	4	6	12	50	58	2017
Computer Networks	4	4	4	74	2	2020
Future Generation Computer Systems	4	4	4	94	175	2019
Journal of Optical Communications and Networking	4	5	5	90	138	2018
IEEE Transactions on Network and Service Management	3	5	5	52	117	2020
Iet Networks	3	4	4	127	18	2018
Internet of Things	3	3	3	172	24	2019
IEEE 28th International Symposium on Industrial Electronics (ISIE)	2	2	2	9	1	2019

The "*Journal of Lightwave Technology*" has demonstrated its influence with 301 commendable citations from just six publications. Interestingly, "*Applied Sciences-Basel*", which began its contributions in 2017, has already published 12 articles, indicating its growing interest in the domain. Despite having only four publications, it is also worth highlighting that "*Computer Networks*" has garnered 74 citations, showcasing the importance of its contributions. The data underscores the pivotal role of these sources in shaping the discourse and research trajectory in the realm of AI in SDN.

Local citations (LC) and total citations (TC) offer unique insights in this context. LC represents the number of times the literature items within the dataset cite a particular source, while TC provides a broader perspective, indicating the overall influence of a source's literature items in the wider academic community. "*IEEE Access*" prominently features a high TC of 984, reflecting its literature's extensive influence. However, its LC of 956 suggests that a considerable number of these citations originate from the dataset, emphasizing its pivotal role in AI in the SDN narrative. In juxtaposition, "*IEEE Communications Surveys and Tutorials*" boasts a TC of 1385 but a notably lower LC of 611, hinting at its literature's expansive reach beyond this dataset. "*Sensors*" presents an interesting case with a TC of 140 but a remarkably low LC of 6, indicating its broader external citations but limited impact references within the dataset. Conversely, "*Applied Sciences-Basel*" demonstrates a harmonious TC and LC, signifying steady acknowledgment both internally and externally.

These observations accentuate the diverse influence of sources in AI on the SDN research spectrum, underscoring the intricate interplay between localized and broader academic impacts. They also offer academicians valuable insights for strategic decision-making in research. They highlight influential journals for publication, emerging trends in AI and SDN, and the varying impact of research within and beyond the immediate academic community. This information is crucial for guiding research focus, identifying collaboration opportunities, and benchmarking academic output, thereby helping researchers stay aligned with the evolving dynamics of the field.

4.1.4. Top Cited Literature Items

Citation metrics offer a lens into the influence and recognition of scholarly works. This section delves into local citations (LC)—citations within the dataset—and global citations (GC)—from all sources. Table 6 showcases the top 15 articles based on their LC, but it is noteworthy that the LC only occasionally mirrors the GC. The normalized local citation (NLC) offers a more nuanced perspective, adjusting for the expected citation rate based on the publication year. Some scholars posit that raw citation counts may be incapable of capturing a paper's impact as effectively as normalized metrics [18].

Table 6. Analysis of the top cited literature items.

Title	Year	LC	GC	NLC
Artificial Intelligence-Enabled Software-Defined Networking: A Comprehensive Overview	2019	7	49	40.44
Towards an Efficient Anomaly-Based Intrusion Detection for Software-Defined Networks [19]	2018	5	34	8.33
Artificial Intelligence-Enabled Routing in Software-Defined Networking	2020	5	16	28
An Intelligent System for Video Surveillance in IoT Environments	2018	4	37	6.67
Cognitive Assurance Architecture for Optical Network Fault Management	2018	3	67	5
QR-SDN: Towards Reinforcement Learning States, Actions, and Rewards for Direct Flow Routing in Software-Defined Networks	2020	3	27	16.8
A Systematic Review of Load Balancing Techniques in Software-Defined Networking	2020	2	21	11.2
SmartBlock-SDN: An Optimized Blockchain-SDN Framework for Resource Management in IoT	2021	2	49	36.8
A Centralized Routing Protocol with a Scheduled Mobile Sink-Based AI for Large-Scale I-IoT	2018	1	24	1.67
Multidisciplinary and Historical Perspectives for Developing Intelligent and Resource-Efficient Systems	2018	1	15	1.67
A Game Theory-Based Effective Network Management in SDN Networks	2018	1	1	1.67
An Optical Communication's Perspective on Machine Learning and Its Applications	2019	1	190	5.78
Intelligent Quality of Service Routing in Software-Defined Satellite Networking	2019	1	3	5.78
UAVs joint optimization problems and machine learning to improve 5G and Beyond communication	2020	1	25	5.6
How to Mislead AI-Assisted Network Automation in SD-IPoEONs: A Comparison Study of DRL- and GAN-Based Approaches	2020	1	5	5.6

A striking observation is that the article "Artificial Intelligence-Enabled Software-Defined Networking: A Comprehensive Overview" from 2019 leads with seven LCs and a commendable 49 GCs, boasting an NLC of 40.44. In contrast, "An Optical Communication's Perspective on Machine Learning and Its Applications" from 2019, despite having only one LC, has an impressive 190 GCs, reflecting its broader academic influence. Interestingly, 13 out of 15 top-cited articles were published within the last five years, underscoring the burgeoning interest in AI in SDN. This trend, combined with the diverse citation metrics, underscores the evolving and dynamic nature of research in this domain.

Notably, 12 of these 15 top literature items are published by IEEE journals, underscoring IEEE's dominance in AI in the SDN field. Furthermore, while they may have low LCs within this dataset, the articles "Convergence of Edge Computing and Deep Learning: A Comprehensive Survey", "Internet of Things (IoT) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends, and Prospects for Emerging 5G-IoT Scenarios", and "The Future of Healthcare Internet of Things: A Survey of Emerging Technologies" from 2020 have garnered significant global attention with 539, 379, and 304 GCs, respectively.

A significant observation from the dataset is that a vast majority, 451 out of the 474 literature items, received zero LC, indicating limited internal referencing within the dataset.

Moreover, 139 literature items are uncited in the GC metric, pointing to a lack of external recognition for these works.

4.1.5. Top Contributing Affiliations

The number of publications from an affiliation is a metric to gauge its academic influence and contribution to AI in the SDN domain. Figure 4 showcases the top 16 affiliations based on the number of articles published by their academic members. Out of the dataset, there were 796 affiliations, with a striking observation that over 72% of these affiliations contributed only a single document.

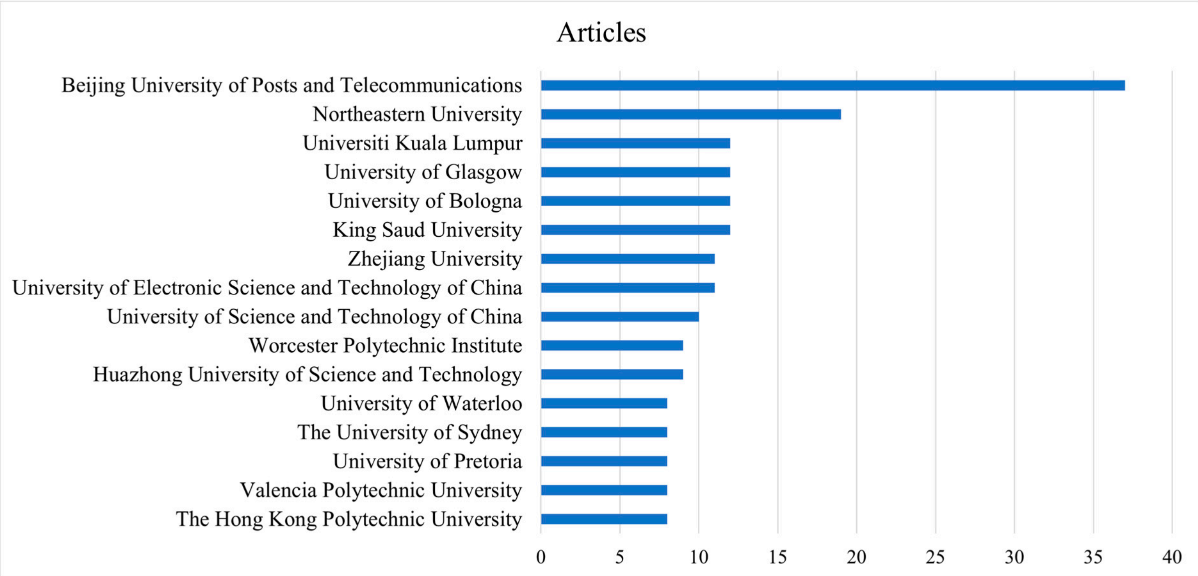


Figure 4. Top contributing affiliations based on the number of articles.

The Beijing University of Posts and Telecommunications in China leads the pack with 37 articles. The rank is followed by Northeastern University in the US, with 19 articles. The list also features other prominent institutions like King Saud University (KSA), the University of Bologna (Italy), and the University of Glasgow (Scotland), each contributing 12 articles. It is noteworthy that while Zhejiang University and the University of Electronic Science and Technology of China, both from China, have made substantial contributions, institutions from diverse regions like Universiti Kuala Lumpur (Malaysia), Worcester Polytechnic Institute (US), and the University of Sydney (Australia) also feature prominently.

Affiliation analysis provides academicians in this field with key insights. A concentrated pool of leading institutions, like the Beijing University of Posts and Telecommunications and the Northeastern University, indicates where significant research is being conducted. Despite the dominance of single-document contributors, the global spread of contributing affiliations highlights a worldwide interest in the field, suggesting opportunities for international collaborations and a need for broadening research participation. This information is crucial for academicians to identify potential research hubs and collaboration networks and understand the geographical dynamics of the field's academic landscape.

A closer look reveals a diverse geographical spread among the top contributors. While China remains a dominant player with five institutions in the top 16, there is a notable presence in countries like the US, Italy, Scotland, Malaysia, Spain, South Africa, Australia, and Canada. This distribution suggests a global interest in and contribution to AI in the SDN research domain. The subsequent sections will delve deeper into contributions by country.

4.2. Country Analyses

The landscape of AI in SDN research is shaped by contributions from various countries. In the data set under analysis, 61 countries have made their mark. Evaluating the contributions of each country offers a panoramic view of global research dynamics, highlighting the influence and commitment of different nations to this domain. This section delves into two distinct metrics: countries' productivity and collaborations.

4.2.1. Countries' Impact and Productivity

In this section, each document is attributed to the country of its primary author, ensuring that every document is associated with just one country. This method facilitates the calculation of single-country publication (SCP) and multiple-country publication (MCP) metrics. The MCP ratio further refines our understanding of collaboration levels among countries. Additionally, this section delves into the total citation counts and the average citations per document for each nation, as detailed in Table 7.

Table 7. Analysis of countries' impact and productivity.

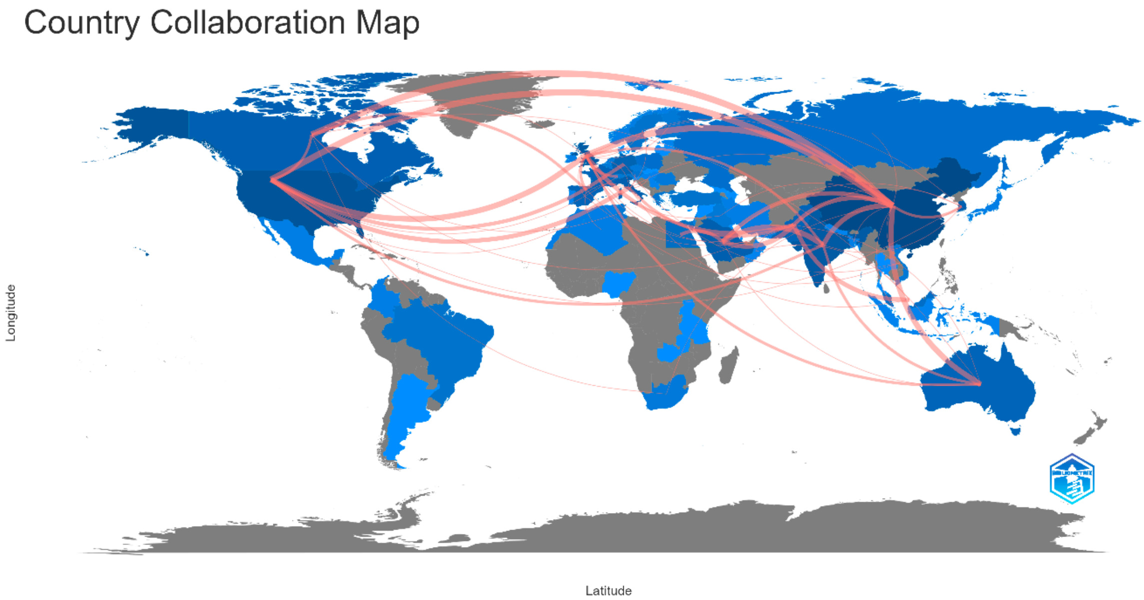
Country	No. of Publication	Freq. Appearance	SCP	MCP	MCP Ratio	Total Citations
China	102	367	71	31	0.304	2507
USA	45	186	37	8	0.178	639
India	32	108	24	8	0.25	60
Republic of Korea	24	68	15	9	0.375	458
Italy	23	86	11	12	0.522	143
UK	22	85	9	13	0.591	381
Spain	20	59	14	6	0.3	293
Germany	18	72	11	7	0.389	168
Canada	12	51	6	6	0.5	208
Poland	12	35	10	2	0.167	128
Saudi Arabia	11	50	5	6	0.545	14
Russia	9	29	4	5	0.556	19
Brazil	7	22	7	0	0	48
France	7	51	4	3	0.429	29
Malaysia	7	25	0	7	1	38

China emerges as the dominant player with 102 publications, followed by the USA, India, Republic of Korea, and Italy. China's literature, cited 2507 times, underscores its significant influence. Meanwhile, despite having fewer publications, the USA boasts 639 citations, emphasizing its pivotal role in AI in SDN discourse. When it comes to sheer productivity, these nations lead, but the dynamics shift when we consider collaboration.

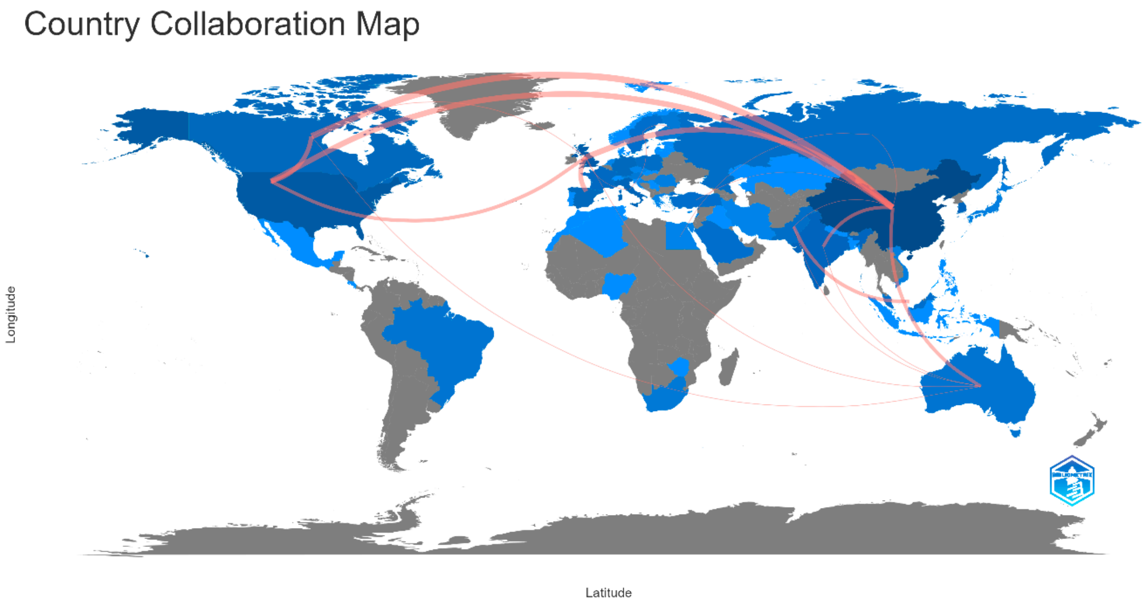
Italy and the UK strongly favor international collaborations, with MCP ratios of 0.522 and 0.591, respectively. In contrast, Malaysia's entire contribution is through international collaborations, reflected in its MCP ratio of 1. Conversely, Brazil has all its literature resulting from internal efforts, with an MCP ratio of 0. The citation count further highlights the influence of these nations. While many countries have made contributions, the leadership of China and the USA in AI in SDN research is undeniable.

4.2.2. Collaboration between Countries

This section utilizes two distinct time frames to analyze the dynamics of collaboration between countries in the field over different periods: 2009–2020 and 2020–2023. These time frames are delineated based on the annual publication growth described in Section 4.1.2. Figure 5 offers a visual representation of these time frames by producing two choropleth maps reflecting the collaborations of the countries from 2009 to 2023. In the 2009–2020 span, prominent collaborations were evident between China and Canada, China and the United Kingdom, China and the USA, and the USA and the United Kingdom, among others. The highest frequency of collaboration was observed between China and Canada.



2009–2020



2020–2023

Figure 5. Countries' collaboration on the AI-SDN topic over the years.

Many more collaborations have emerged in the past three years, as the span from 2020 to 2023 shows. It becomes evident that China continues to be a dominant player in collaborations, particularly with Canada, the United Kingdom, and the USA. Additionally, India's collaborations, especially with Saudi Arabia, have emerged prominently. The USA's collaborations with the United Kingdom and Italy also stand out. Notably, collaborations involving Saudi Arabia, such as with Pakistan and Egypt, have gained momentum in this period. Although European countries like Italy, France, and the United Kingdom show consistent collaboration, Russia's interactions, particularly with China, remain minimal.

Such information offers academicians critical insights into the field's global dynamics. The dominance of countries like China, the USA, and India in publications and citations highlights key regions of academic influence and potential research opportunities. The evolving collaboration patterns, with a notable increase in international partnerships, underscore the importance of cross-border collaborations for advancing the field. Similar to the contributing affiliation analysis, academicians must identify leading research hubs, potential collaborative networks, and emerging trends in global research contributions and partnerships in AI-SDN.

4.3. Authorship Analysis

Various metrics are employed to gauge the scientific production and influence of authors in academia, including the h-index, g-index, m-index, total citation count (TC), local citation count (LC), and NP (number of papers). This section delves into exploring these metrics, focusing on four contributing authors in the realm of AI in SDN, as detailed in the provided dataset.

The h-index represents a measure where a scientist has "h" papers that have received at least "h" citations each. The g-index is an enhanced version of the h-index, defining the unique largest number in which the top "g" papers have collectively received at least g^2 citations. The m-index, on the other hand, provides a normalized measure of the h-index over the years since an author's first publication. Total citation count signifies the cumulative number of times an author's work has been cited, and NP indicates the number of papers authored by the individual.

Upon examining the metrics from the updated dataset, several noteworthy observations emerged. A significant 85% of the authors have just one publication in the domain of AI in SDN. Furthermore, an overwhelming 99% of the authors have an article fractionalization of less than 1. The phenomenon prompts inquiries about the nature of these publications. Are academic authors producing a plethora of distinct articles, or are they predominantly co-authoring, leading to a high number of shared contributions without much individual input? Notably, the most minimal article fractionalization observed in the dataset is 0.1, indicating that ten authors collaboratively wrote an article. Table 8 tabulates the most impactful authors in this field. It is noticeable that the two most influential LC authors (Majd Latah and Levent Toker) had only two publications, so they were not on the top impact author list. The data suggests a collaborative trend in the field, yet it does not point to any single dominant figure in AI in SDN research.

Table 8. Authorship analysis based on publication metrics.

Author	NP	h_Index	g_Index	TC	LC	PYS
Adnan Abu-Mahfouz	6	3	6	36	0	2017
Mohammad Riyaz Belgaum	4	3	4	30	2	2019
Muhammad Ali Imran	4	3	4	98	0	2020
Shahrulniza Musa	4	3	4	30	2	2019

4.4. Content Analysis

In this section, we discern the topic trends by harnessing advanced Natural Language Processing (NLP) techniques. Using NLP, we identified important author keywords and visualized the relationship between these keywords using network graph analysis. Additionally, a deeper analysis of the content discussed the mobile communications subdomain in AI-SDN as a sample study.

4.4.1. Author Keywords

The co-occurrence network, derived from author keywords, provides a comprehensive snapshot of the primary themes within AI-SDN. The co-occurrence network analysis evaluates the collective relationship between the terms based on their paired presence within the author keywords. This section adopts the network graph approach to visualize and evaluate this metric. The graph clusters the keywords by coloring the nodes. Each node has its own individual size, representing the node's weight in the graph. Also, each node has several edges with different thicknesses based on the bilateral co-occurrence weight with other nodes. The depiction of authors' keywords and their co-occurrences is illustrated in Figure 6.

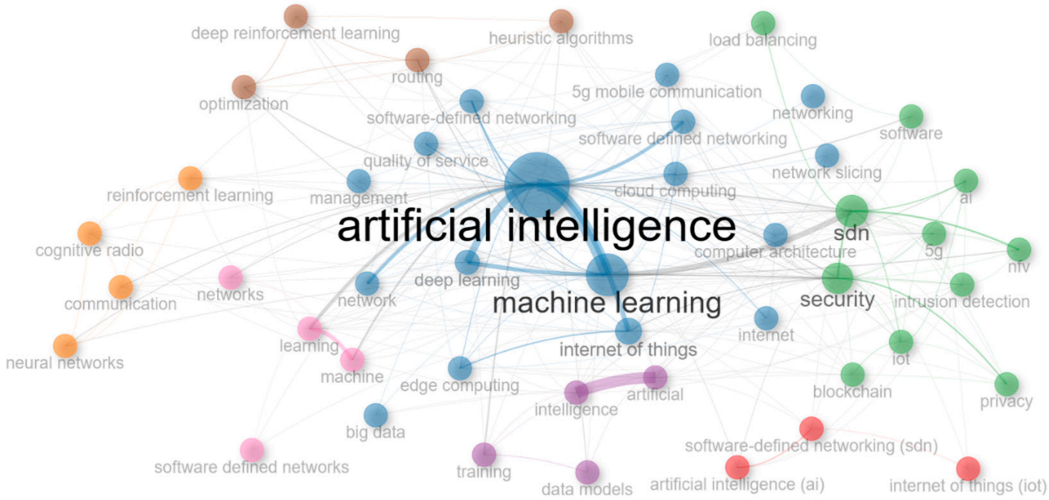


Figure 6. Network illustration of author keywords.

The blue cluster stands out, with "machine learning" and "deep learning" as its pillars, emphasized by their notable betweenness and centrality values. "Internet of Things" and "cloud computing" further enrich this cluster's significance. The green cluster centered around "security" underscores the integration of security aspects with emerging technologies such as "5G" and "blockchain". Delving deeper, the orange cluster featuring "neural networks" and "reinforcement learning" highlights the advanced AI techniques in SDN. Meanwhile, the brown cluster with keywords like "routing" and "deep reinforcement learning" suggests a focus on sophisticated learning techniques for network optimization.

The term "security" emerges as a paramount concern, emphasizing the potential vulnerabilities when melding AI with SDN. The mention of intrusion detection further accentuates the need for robust mechanisms to detect and counteract unauthorized access or breaches. Ensuring a consistent quality of service in an SDN environment augmented by AI presents its challenges, as does the task of load balancing to ensure optimal performance and resource utilization. The keyword privacy brings to the fore the significant concerns surrounding data protection, especially given the vast amounts of data processed by AI. Additionally, network slicing, which pertains to the creation of isolated network segments in a virtualized environment, and optimization, which revolves around achieving the best configurations and solutions in SDN, further highlight the multifaceted challenges of this domain. These terms collectively paint a picture of the complexities and considerations that researchers and practitioners must navigate in the evolving field of AI in SDN.

The field of SDN in AI has seen a dynamic shift in research topics over the years. Figure 7 depicts the topic trends drawn from the authors' keywords for the literature items. The line represents a topic trend timeline, and the circle radius is proportional to the number of documents that follow a topic trend. The darker the circle's color, the more citations a topic trend receives.

Dominating the landscape are themes like "machine learning", "security", and "deep learning", which have been prevalent between 2020 and 2022, emphasizing the growing integration of AI techniques in SDN. Emerging trends like "cybersecurity" in 2023 and the consistent relevance of "cloud computing" from 2020 to 2023 highlight the evolving intersections of SDN, AI, and other technologies like the Internet of Things (IoT).

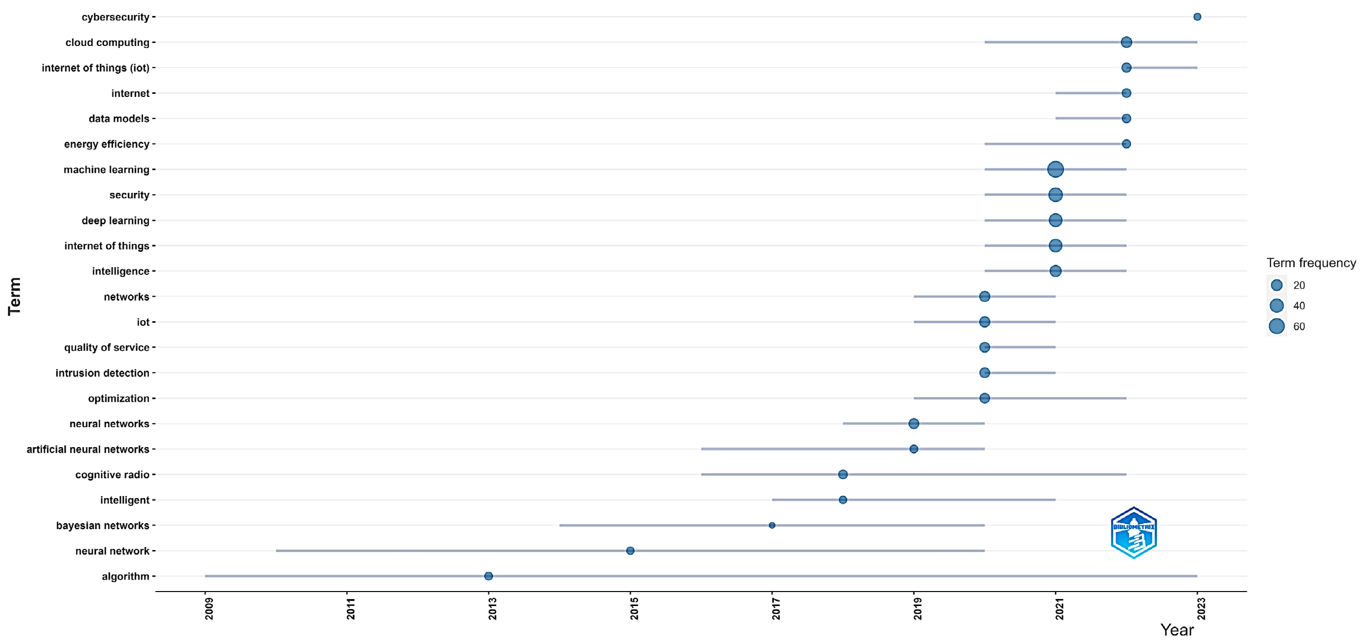


Figure 7. Analysis of author keywords from the dataset.

Historical data reveals a transition from traditional neural network models around 2018–2020 to more advanced AI techniques in recent years. Meanwhile, "energy efficiency" and "quality of service" indicate niche research areas addressing specific SDN-AI challenges. The prominence of these themes suggests a future research trajectory focused on integrating emerging AI techniques with SDN, especially in the cybersecurity and IoT realms, and exploring cloud-based SDN solutions augmented by AI.

Delving deeper into the Mobile Communications sub-domain within AI-SDN, our analysis of author keyword trends, based on 48 literature items, offers a more focused perspective on this specific area. The trend analysis, visualized through a co-occurrence network density graph in Figure 8, reveals key themes and their evolution over time. Notably, "security", "artificial intelligence", and "5G mobile communication" have shown a consistent upward trajectory from 2020 to 2022, underscoring their growing importance in the field. The emergence of "privacy" in 2021, peaking in 2023, aligns with the increasing focus on data protection in mobile networks. Meanwhile, "machine learning" and "deep learning" remain strong, reflecting the ongoing integration of advanced AI techniques in mobile communication. Furthermore, the recent rise of the keywords "network slicing" and "resource management" highlights new areas of interest in optimizing 5G networks and wireless systems. The author's keyword trend analysis complements our broader findings. It sharpens the focus on mobile communication, indicating a clear shift towards integrating AI with 5G technologies and addressing security and privacy challenges in this rapidly evolving domain.

4.4.2. Keywords Plus

Alternative methods exist for examining the content of literature items in the dataset under scrutiny, one notable approach being Keywords Plus. Leveraging a unique algorithm crafted with the expertise of Thomson Reuters' editorial team, Keywords Plus is produced for each literature piece, drawing from its content and the titles of its references [20,21]. This algorithm yields a standardized set of keywords, deeply highlighting the essence of the literature, as shown in Table 9.

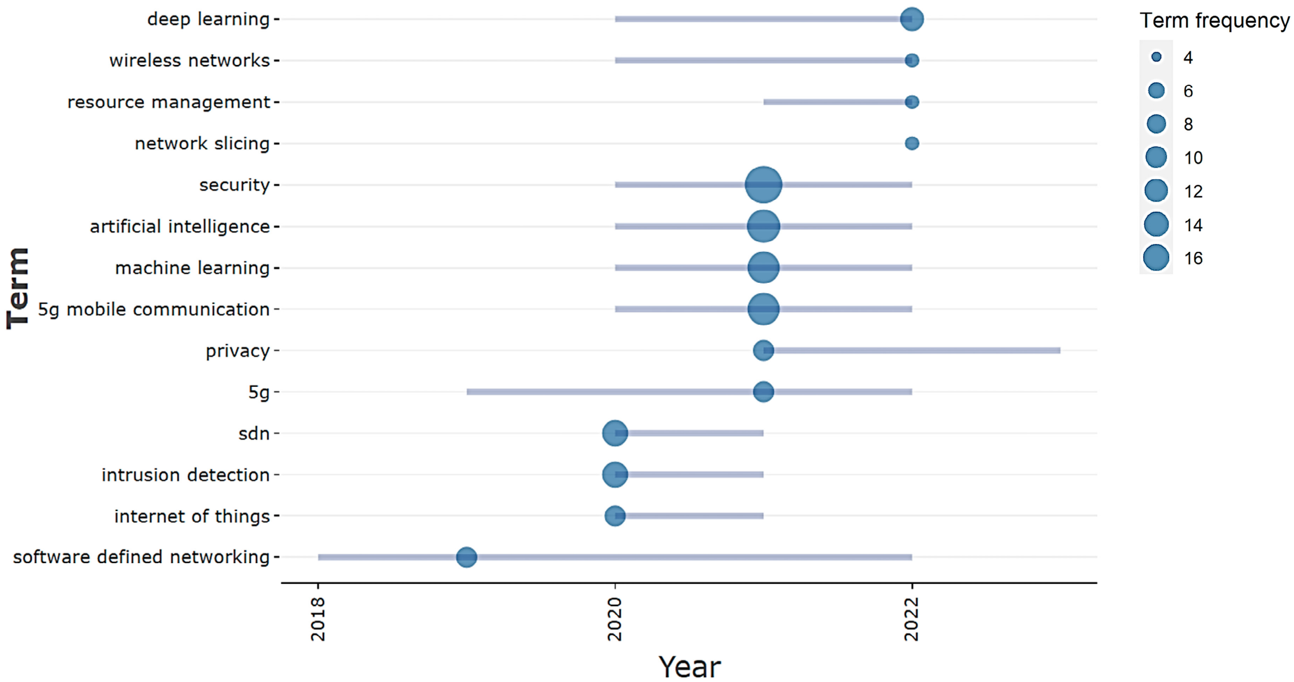


Figure 8. Analysis of author keywords in the mobile communications sub-domain.

Table 9. Keywords Plus analysis of the dataset.

Term	Occurrence	Term	Occurrence
Internet	51	5G	18
Architecture	37	Communication	16
Neural networks	35	Prediction	14
System	33	Security	14
Management	28	Optimization	14
Challenges	22	Intrusion detection	14
Algorithm	26	Blockchain	12
Network	23	Classification	11
Framework	19	Attacks	10
Model	18	Design	10

This section uses two metrics to analyze and visualize Keywords Plus. The first metric is the frequency evaluation of each keyword, which Figure 9 illustrates using the word-cloud visualization. It offers a multifaceted understanding of the evolving research landscape of Software-Defined Networking (SDN) in artificial intelligence (AI). Dominant keywords such as “internet”, “architecture”, and “neural networks” are consistently emphasized, underscoring the foundational and technical dimensions of SDN in AI. The WordCloud further enriches this perspective by introducing terms like “resource allocation”, “wireless networks”, and “anomaly detection”, hinting at the importance of efficient resource utilization and the integration of AI with wireless SDN solutions. Concurrently, terms like “challenges”, “security”, and “intrusion detection”, which resonate across analyses, accentuate the pressing need to address security and systemic challenges.

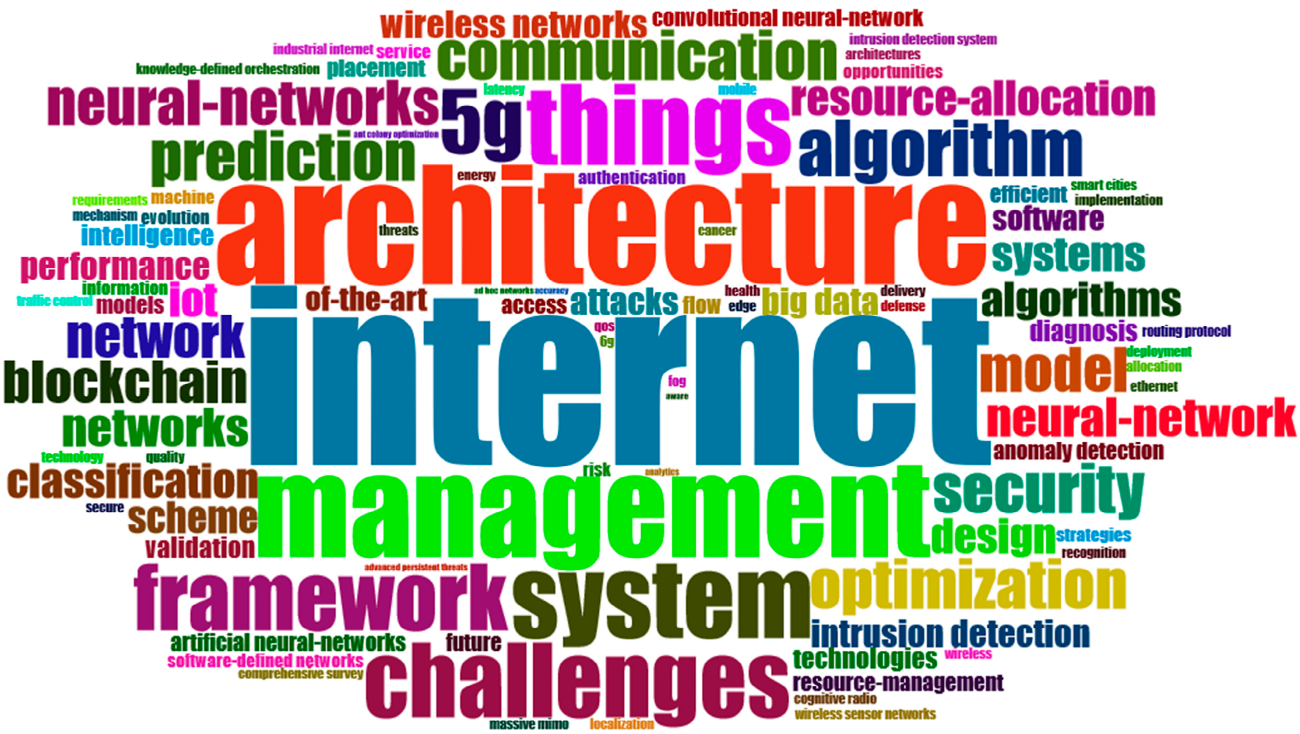


Figure 9. Keywords Plus analysis of the dataset.

Research prospects in SDN and AI are multifarious. On the one hand, there is a palpable drive towards refining architectural and system designs, focusing on integrating advanced AI-driven neural network models for enhanced SDN functionalities. Conversely, the consistent emphasis on security, complemented by WordCloud's highlight of practical and application-oriented terms, underscores the field's commitment to addressing challenges, especially those related to security. As AI techniques, including "prediction", "classification", and "optimization", become more sophisticated, their application in identifying and mitigating network threats, as well as optimizing resource management, is poised to be at the forefront of future research endeavors. This synthesis of insights paints a holistic picture of a domain deeply invested in foundational exploration and pragmatic solutions.

In our focused analysis of mobile communications within AI-SDN in Figure 10, we uncover distinct thematic patterns using a co-occurrence network density graph on a subset of 48 literature items. Central to the research discourse are high-density keywords like "internet", "system", "big data", "SDN", and "intrusion detection", indicating these areas as foundational pillars in the field. In contrast, emerging yet less integrated themes such as "artificial intelligence", "5G", and "wireless networks" exhibit lower density, signaling potential growth areas. Additionally, the peripheral presence of "anomaly detection", "architecture", and "flow" suggests their specialized but currently less emphasized roles. This analysis complements our broader Keywords Plus findings and provides critical insights into the evolving priorities and future directions in mobile communications research within AI-SDN.

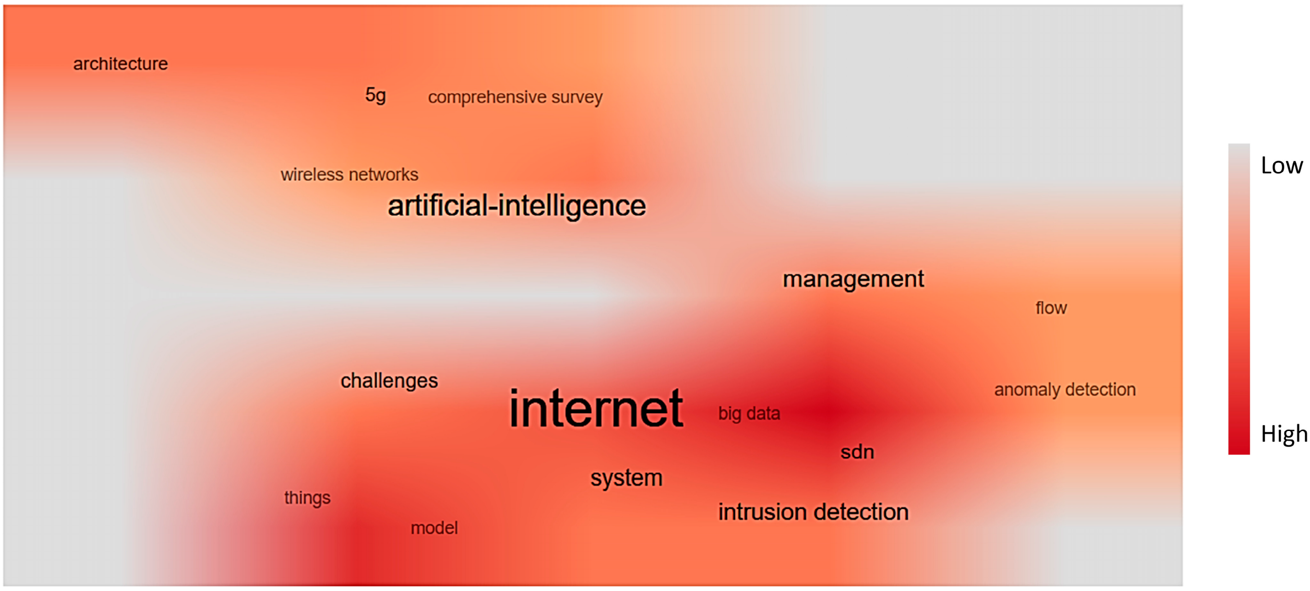


Figure 10. Density graph of Keywords Plus analysis in the mobile communications sub-domain.

4.4.3. Keyword Dynamic Analysis

This analysis focuses on "mobile communication" within the AI-related SDN field. We analyzed a subset of 48 literature items out of 474. Utilizing a Three-Fields Plot, we examine the interplay between countries, keywords plus, and author keywords, revealing the global research dynamics in this niche area. The plot in Figure 11 highlights 15 key countries, with China, Finland, the USA, and Malaysia leading in prominence. Notably, China shows a comprehensive engagement in AI-SDN research, connecting to almost all keywords on both sides of the plot. This analysis indicates the broad spectrum of research interests within the field. In contrast, the USA displays a unique pattern, with no connections to the "Keywords Plus" field, suggesting a more focused or divergent research approach.

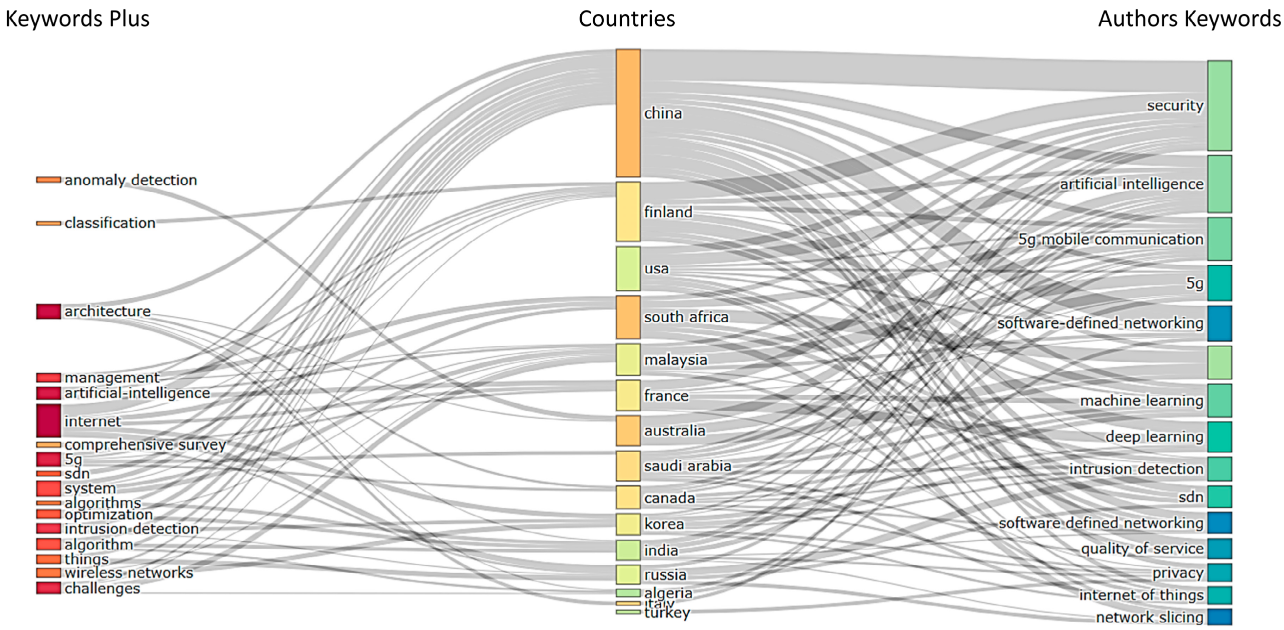


Figure 11. Keyword dynamics analysis relation between authors and countries.

The analysis also uncovers thematic focal points in AI-SDN research. Security is a universal theme linked to all countries, highlighting its global significance. The '5G' keyword, indicating a regional focus, sees contributions mainly from Malaysia, Saudi Arabia, Australia, India, and China, suggesting regional technological advancements or policy priorities. Australia's exclusive contribution to "anomaly detection" points to its niche expertise. Meanwhile, Malaysia's strong association with the "challenges" keyword underscores its role in addressing AI-SDN research challenges. These insights reflect the geographical and thematic diversity in AI-SDN research and the interconnected nature of this evolving field, offering a roadmap for future research directions and international collaborations.

4.4.4. Abstract Analysis

Abstracts of articles offer a holistic overview of scholarly literature, encapsulating the research issue, the overarching objectives, the methodology employed, and the principal findings. Delving into these abstracts furnishes profound insights into prevailing research trajectories and pinpoints the SDN and AI fields. In this section, we discern the thematic map from the abstracts of the literature by harnessing advanced NLP techniques. The analysis employs bigram and tokenization models for the meticulous preprocessing of the abstract data, as illustrated in Figure 12.

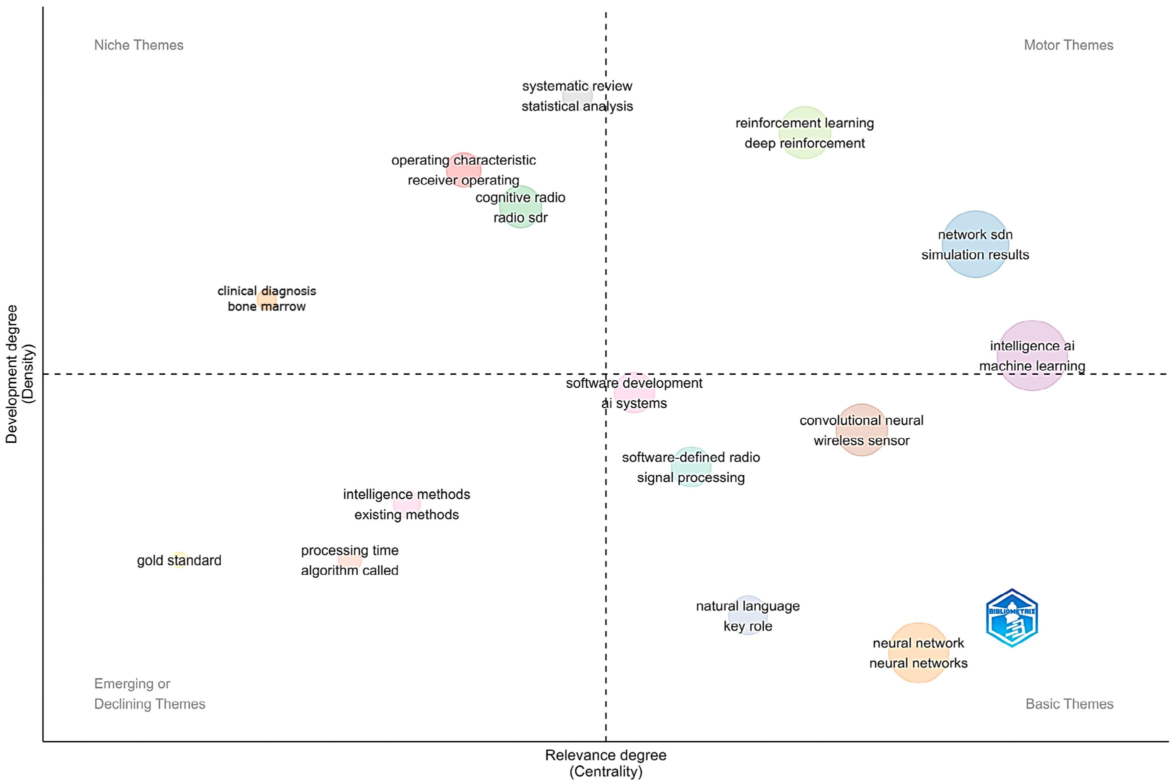


Figure 12. Thematic map of abstract content analysis.

Representing these data into a thematic map provides a comprehensive understanding of the research trajectory in SDN integrated with AI. This evaluation is inspired by [22]. In this section, the thematic map visualizes four typologies of themes based on abstract content analysis and clustering. The thematic map clusters and their indications are explained as follows:

- Quadrant Q1—Core Theme. This theme emphasizes the evolution of SDN systems towards autonomy, with AI-driven optimizations like dynamic routing. The focus is on making networks self-adaptive, but challenges like real-time algorithmic operations in vast networks remain. This quadrant suggests a move towards more resilient and efficient autonomous SDN systems.

- Quadrant Q2—Niche Theme. This quadrant highlights integrating cognitive radio technologies with SDN, promising dynamic spectrum management. The potential lies in dynamic frequency selection in wireless networks, but interoperability challenges between cognitive radios and SDN infrastructures are evident. The emphasis is on performance evaluation and effective AI-driven enhancements.
- Quadrant Q3—Underdeveloped Theme. The third quadrant underscores the development of AI methodologies tailored for SDN to enhance real-time operations. The goal is to reduce processing times with applications like fast anomaly detection. However, balancing computational efficiency with accuracy in AI-driven operations is challenging, emphasizing the importance of speed in SDN systems.
- Quadrant Q4—Peripheral Theme. Quadrant four depicts a multidisciplinary approach to SDN, integrating diverse AI techniques. Prospects include voice-command-driven configurations and image-based traffic analysis. Challenges arise from integrating diverse AI techniques, suggesting a future of holistic SDN solutions.

The thematic map analysis of SDN in AI reveals a trajectory towards autonomous and efficient network systems underpinned by diverse AI methodologies. Challenges like real-time operations and interoperability emerge as the field gravitates towards integrating advanced AI techniques. Addressing these challenges will be pivotal for the holistic evolution of SDN systems in the future.

5. Research Advancements in AI-SDN

Network technology has grown tremendously with the introduction of SDN in the last decade. The innovation in SDN's centralized and programmable network controls facilitates the rapid development of new network services and protocols [7]. These programmability traits lead to more service automation, which reduces the network administrator's workload and enables rapid network changes. Additionally, adding intelligence to the network allows for better decision-making, as AI helps make faster adjustments and increase efficiency. For example, AI improves network effectiveness through smart load balancing, routing, security, and adaptive resource management [23]. Therefore, to support the widespread adoption of SDN through industry and the academic world, a detailed overview of the field is important, which is addressed by this study.

From the results of the previous section, AI-based efforts in SDN comprise several key terms, such as "architecture", "algorithms", "challenges", and "internet". The architecture term defines the conceptual structure and organization of the SDN. Algorithms define the process or rules that need to be followed for the calculation to solve the problem, which is the core of any AI algorithm. The challenge keyword questions the current state of the field and reveals weaknesses that need solving. The internet keyword highlights the key area that receives the benefit of better AI-SDN systems, which comprises multiple applications and real-world services that make up the Internet. Together, these keywords signify the premise of the AI-SDN idea: to improve networks and the Internet by overcoming the challenges using AI-based algorithms.

Although previous studies investigated the AI-SDN field in their specific scope and perspectives, few studies address the connection between these perspectives [6,7]. Therefore, it is important to understand the current paradigm in AI-related SDN efforts to grasp the domain fully. This study plays an essential role in establishing knowledge by elaborating on the taxonomy in Figure 13, which summarizes the general composition of the field.

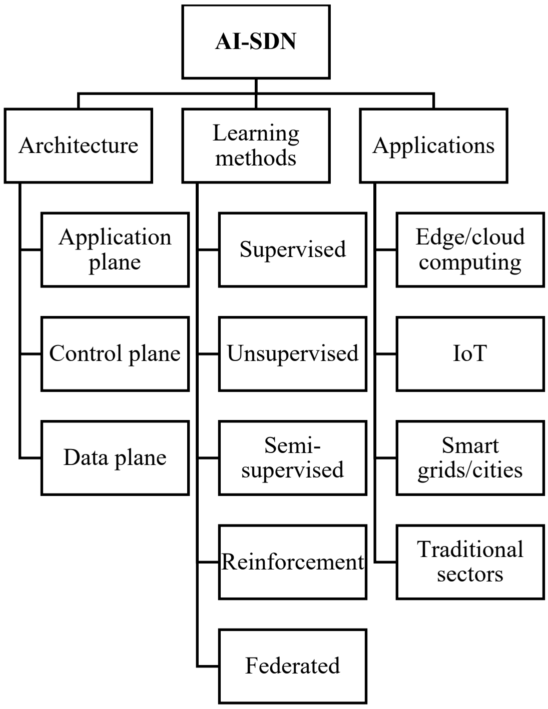


Figure 13. Taxonomy of AI-SDN studies.

5.1. Architecture

The architecture of an AI-SDN infrastructure consists of multiple building blocks, as shown in Figure 14. Originally, these components formed the basis of an SDN, which is the physical infrastructure for the network, with the integration of AI operations in each component turning it into the AI-SDN paradigm. The hierarchical top-down structure for SDN consists of the application plane, control plane, and data plane, which are connected using specific communication interfaces known as the northbound and southbound interfaces.

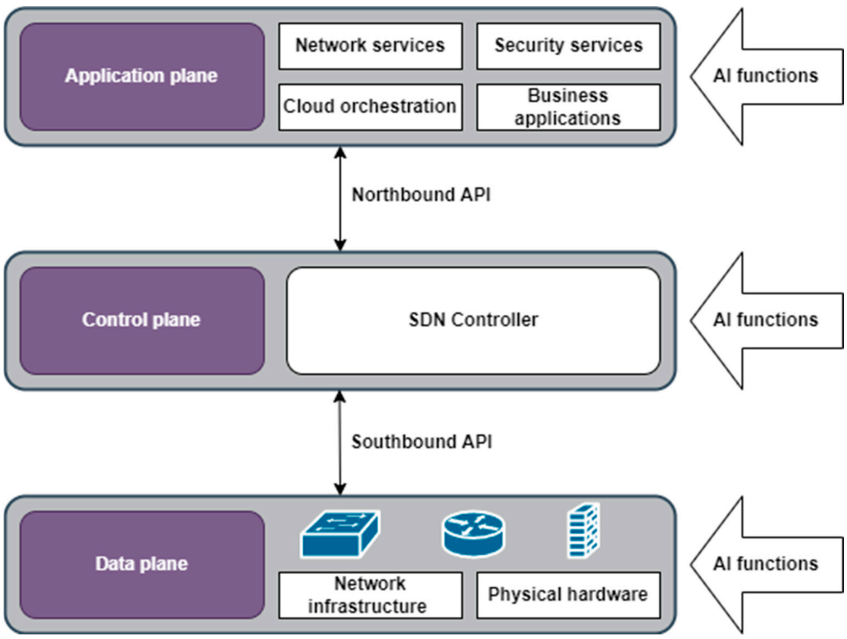


Figure 14. The AI-SDN infrastructure.

5.1.1. Application Plane

The application plane sits on the topmost layer of the SDN architecture. The plan mainly contains high-level business logic and applications. These applications determine the network behavior to achieve business goals by sending specific requirements to the control layer that handles the network functions via the Northbound Interface (NBI). The AI integration in the application plane significantly enhances the SDN capabilities to respond to changing network conditions, user requirements, and security threats. The following techniques enhance and optimize SDN applications using AI.

(a) Intelligent applications

The SDN applications benefit from integration with AI technology due to the development of new applications that adapt to changing network conditions, user demands, and business requirements. As a result, SDN becomes agile, dynamic, and capable of making decisions thanks to AI-driven insights. For example, recently, the world saw an unprecedented impact on the industrial ecosystem due to the COVID-19 pandemic. To overcome the contact restrictions imposed for the outbreak, the authors proposed an intelligent and automated framework to manage IoT ecosystems supporting Industry 4.0 technologies [24]. The intelligent applications allow SDN to operate with minimum human intervention, thus experiencing fewer disruptions and increasing productivity.

(b) Traffic prediction and management

The AI-driven applications enable the SDN to predict traffic patterns and adjust the network configuration automatically. Predicting traffic patterns leads to an efficient network that uses optimal resources, resulting in optimized network performance. One example of the work in this area by [25] highlights the importance of traffic prediction and management. The authors deploy a traffic prediction module to reduce network congestion, lowering latency and packet loss. Subsequently, the network throughput experiences an increase, justifying the performance optimization and efficiency. Furthermore, SDN environments can be managed efficiently with proper management mechanisms, such as control channel isolation [26]. The correct management approach improves control message processing latency to address performance issues in the network hypervisor.

(c) Quality-of-Service (QoS) enhancement

The integration of AI in SDN increases network capabilities to provide reliable services. One of the requirements of a reliable network service is to ensure that the QoS requirement is always met. An efficient load-balancing mechanism is necessary to achieve the QoS requirement in high-volume networks. Deploying AI techniques and algorithms such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) ensures efficient load balancing between network resources [27]. These techniques guarantee maximum utilization of available resources, thus reducing the overall expenditure on network management and enabling automation.

5.1.2. Control Plane

The control plane is known as the 'brain' of the network and is responsible for traffic-forwarding decisions. This plane receives the network requirements from the applications via the NBI and translates the abstract requirements into a network function. The SDN controller is the most important element in the control plane, as it determines the action when a packet enters the network. The controller sends the appropriate action as an instruction to the forwarding devices in the data plane via the Southbound interface (SBI). The process of instructing actions to forward devices is enhanced with the help of AI to make better decisions in SDN. The following techniques highlight an example of AI integration in the control plane.

(a) Dynamic routing

AI techniques can be utilized to optimize routing decisions in SDN. Features such as network conditions, traffic patterns, and bandwidth utilization are some features that feed into the AI algorithms to determine the most efficient data paths. Subsequently, the algorithms result in lower latency and better network performance. One example of such work is [28], which focused on an AI-based routing mechanism for congestion avoidance in SDN. The study integrates a neural network mechanism to provide self-learning and decision-making for routing.

(b) Fault detection and recovery

Network deployments always face the risk of failure and, therefore, require appropriate action for detection and recovery. These actions may come in the form of link monitoring to detect faults or rerouting to avoid affected areas. In order to provide a faster response to faults, researchers adopt AI solutions into SDN. For example, the study by [29] mitigates failure in SDN controllers using an AI algorithm to anticipate the controller load. The approach allows SDN to detect potential failures and take preemptive action to mitigate the risk.

(c) Security

The security of a network can be bolstered using the correct AI approach to detect unusual patterns or anomalies. These abnormalities may indicate the presence of cyber-attacks or intrusions, which requires the control plane to take immediate action to secure the network as soon as the threat is detected. In SDN, DDoS threats are a popular topic among researchers, with the recent approach of machine learning and deep learning showing more dynamic, efficient, and intelligent solutions [30]. Using the right feature set and learning model prevents attacks and protects the SDN from failures.

(d) Load balancing

As the network demands expand to cater to the needs of various entities, traffic distribution becomes a challenge that negatively impacts performance without proper handling. Various load balancing mechanisms attempt to enhance the network's efficacy to address the issue, ensuring balanced resource usage. One of the approaches involves implementing AI in load balancing to overcome the challenges. The topic attracts numerous researchers to focus on it, as shown in a survey article by [31]. The article summarized the AI-based load-balancing methods in SDN from various perspectives, including the strengths and weaknesses of load-balancing using AI in SDN.

5.1.3. Data Plane

The data plane is responsible for the actual data packet transmission between network devices based on the routes defined by the control plane. The data plane receives the rules and routes from the controller via the SBI to determine what happens to a packet once it enters a network. The integration of AI into the data plane aims to enhance the efficiency, performance, and security of data packet transmission using the following approaches, as summarized below:

(a) Data traffic management

Optimizing the packet flow in SDN allows efficient network traffic and avoids congestion. The AI optimization methods in the SDN data plane may involve techniques such as optimal path selection and switch queue management. For example, [32] proposed a fast algorithm to schedule real-time flows by eliminating scheduling conflicts. Additionally, various implementations of data traffic management in AI-SDN, as elaborated by [33], include traffic forecasting and flow control using AI algorithms.

(b) Fault detection and recovery

A network must have failure detection and recovery mechanisms to ensure reliable operation. Regarding AI-SDN, multiple approaches have focused on predicting, detecting, and recovering from failures by adopting various ML algorithms [33–35]. These earlier works advanced SDN operations, leading to self-healing and the network's automotive capabilities.

(c) Performance optimization

AI provides tremendous assistance in continuously monitoring and optimizing the performance of the SDN data plane. For example, automatic load balancing to optimize path usage reduces latencies and energy consumption, leading to cost-effective solutions [36]. Additionally, the optimization maintains high QoS and scalability as the network can manage growing data traffic.

5.2. Learning Methods

Various learning methods are employed throughout the development of AI-SDN research to enhance network performance, security, and network management. These methods leverage the ability to learn from available data, identify patterns, predict an outcome, and make decisions with minimal human intervention. The identified learning methods in AI-related SDN are as follows:

5.2.1. Supervised

The supervised learning approach in SDN involves training an algorithm with labeled data, meaning the data includes both the input and corresponding output. It is applied in scenarios where the input-output relationship of the data is sufficiently known. Supervised learning can be used for tasks like traffic classification and anomaly detection. For instance, a trained AI model using labeled and historical traffic data performs a classification on new traffic to identify whether the traffic is normal or malicious [19]. The efficiency of supervised learning depends on the availability of extensive and accurate data, which can be difficult to acquire.

Table 10 below illuminates existing works on AI-SDN using the supervised learning approach.

Table 10. Examples of supervised learning in AI-SDN.

Reference	Description	Algorithm/Methodology	Findings
[37]	Intrusion detection in IoT	SVM	The detection accuracy of anomalies achieved was 99.71%
[19]	Intrusion detection	NN, LDA, DT, ELM, SVM, KNN, AdaBoost, RustBoost, and LogitBoost	Bagging and boosting algorithms have a confidence level >99.5%; ELM has the best testing time
[38]	Traffic demands in the mobile network operator	Neural networks	Reduced the optimality gap below 0.2% and 0.45%
[39]	Malware detection	RBF-SVM	Detection rate of 80% for malware and 95% for normal traffic

5.2.2. Unsupervised

Unsupervised learning takes on a different approach compared to supervised learning. It operates on unlabeled data by identifying patterns and relationships between data points without pre-defined or known outcomes. The unsupervised learning algorithms offer benefits, particularly when the labeled data is scarce or the objective is to discover patterns or anomalies [36]. However, the approach poses some challenges that need attention, such as interpreting results. The patterns identified by the algorithms are unlikely to be immediately meaningful, which might require extra analysis. Also, noise and incomplete data may lead to misleading interpretations.

Table 11 lists existing works on AI-SDN using the unsupervised learning approach.

Table 11. Examples of unsupervised learning in AI-SDN

Reference	Description	Algorithm/Methodology	Findings
[40]	Attack pattern recognition for SDN security	Outlier detection algorithms	Characterize attack scenarios with up to 99.05% similarity between the FTP and SSH Patator attacks
[41]	Efficient routing paths	K-Means	K-Means outperforms cosine similarity for the speedup ratio
[42]	Intelligent routing for privacy and compliance	Ant colony optimization	Evaluated 10 risk parameters. ACO with risk parameters performs better than ACO alone
[43]	Traffic classification	K-Means	Identified 12 unique flow classes

5.2.3. Semi-Supervised

The combination of supervised and unsupervised learning culminates the characteristics of both techniques into a beneficial solution called the semi-supervised approach. It operates on the principle of combining labeled and unlabeled data, which is particularly valuable when labeled data is difficult to acquire in the abundance of unlabeled data. In SDN, the advantage of having semi-supervised AI is that it can leverage the limited labeled data, especially for network traffic classification functions. The semi-supervised approach overcomes the diverse challenges in applications, protocols, and user behavior that require a comprehensive training data set. However, the approach requires careful consideration of data consistency between labeled and unlabeled data to avoid erroneous models.

Table 12 below describes the existing works in AI-SDN that adopt the semi-supervised learning technique.

Table 12. Examples of semi-supervised learning in AI-SDN.

Reference	Description	Algorithm/Methodology	Findings
[44]	Intrusion detection	Semi-supervised active learning	Highest accuracy (96%) compared to FedAvg and FL-SSL for intrusion detection
[45]	DDoS detection	SVM	Accuracy, precision, and recall results are 99%, 66%, and 66%, respectively
[46]	Traffic classification for QoS	Heteroid tri-training	Heteroid tri-training improves AUC by 11% compared to common tri-training
[47]	Traffic classification	Laplacian SVM	Outperforms the K-means; accuracy exceeds 90%

5.2.4. Reinforcement

Reinforcement learning involves a decision-making process where an AI agent learns to achieve a goal by interacting with the environment, specifically the SDN. The interaction between the agent and network objects, such as traffic, devices, and conditions, allows the agent to make sequential decisions while receiving feedback as rewards or penalties. For example, an adaptive routing mechanism using a reinforcement learning agent continuously monitors network conditions, congestion, latency, and packet loss to decide the best approach to redirect traffic flow. When the decision is made, it receives feedback based on the current network performance and makes further adjustments if necessary. Over time, the agent identifies the optimal routing conditions under various network parameters, making the SDN most efficient. However, the complexity of adaptation and the requirement of a suitable reward structure still present a unique challenge that may uncover new opportunities.

Table 13 lists the use cases of the reinforcement learning method in SDN.

Table 13. Examples of reinforcement learning in AI-SDN.

Reference	Description	Algorithm/Methodology	Findings
[48]	Routing for satellite networks	Unspecified	Throughput is 8% higher compared to traditional routing
[49]	Routing QoS	Multistep DRL (AQMDRL)	Superior to other DRL algorithms (TD3, DDPG, and OSPF) in load balancing and transmission delay
[50]	Vehicular network routing	SD-QGrid (Q-learning)	Improved performance for less than 2% overhead, 10% transmission ratio, and reduced end-to-end delay by 25% compared with QGrid and advQGrid
[51]	Multipath routing	Markov Decision Process and Q-learning	Superior in jitter and packet loss rate compared to Dijkstra and ECMP

5.2.5. Federated

The federated learning approach trains AI algorithms in a distributed manner, so the devices or nodes holding the data samples stay on the node. This means that the data on the node resides locally, which secures the data, preserves the privacy of sensitive data, and makes resource utilization more efficient. It is a game-changer, allowing AI model implementation in secure, private, lightweight, and regulated environments. In scenarios such as lightweight IoT and edge SDN, the devices involved usually generate vast amounts of data, and it is impractical to transfer to a central location for processing. Training the models on the local devices significantly improves response times and decreases network load. However, several challenges in federated learning should be addressed, such as the communication mechanisms to ensure consistent device updates and security measures against model poisoning attacks.

Table 14 below highlights the current examples of federated learning methods in SDN.

Table 14. Examples of federated learning in AI-SDN.

Reference	Description	Algorithm/Methodology	Findings
[44]	Intrusion detection	FL-based, semi-supervised active learning	Outperformed the baseline in reducing communication costs by 47%
[52]	Security for satellite-IoT communication	FedAvg	Proposed SDN-FL-based satellite-IoT framework
[53]	Routing in Edge SDN	LSTM	Best model in 4-layer 128-neurons, lowest error

5.3. Applications

The convergence of AI-SDN introduces intelligence into computer networking, enabling a dynamic solution that can adapt, predict, and respond to changes with minimal human intervention. Across the digital landscape of real-world services, AI-SDN finds its benefits in a myriad of sectors, including edge and cloud computing, IoT, smart cities, and other traditional sectors. The presence of AI-SDN in these sectors justifies its importance to technology and demonstrates its necessity for the future. This subsection discusses real-world implementations to observe how technology benefits people.

5.3.1. Edge/Cloud Computing

Edge and cloud computing are revolutionary technologies that decentralized traditional computing architecture's processing power and storage [24]. It allows users to access computer processing power and storage without having physical access to the infrastructure. However, catering to increasing users may lack the necessary efficiency and security of computing resources. To deal with these issues, AI-SDN facilitates the solution to the problems by using intelligence for better resource allocation and improvising security measures in edge and cloud computing.

(a) Resource allocation

Efficient resource management in edge and cloud computing may sometimes require the devices at the edge to process data closer to where it is generated to reduce network load. AI-SDN provides dynamic management of network resources through smart load balancing of network resources. The AI algorithm receives input from traffic patterns, device processing capacity, and latency requirements for the edge and cloud devices to allow resource allocation between them. The efficient load balancing between them leads to efficient real-time data processing, low latency, and enhanced response times.

(b) Advanced security and privacy

The edge and cloud infrastructure require solid security in place, as the vast amount of data transmitted in the environment presents a multitude of threats. AI-SDN identifies potential security threats via intelligent anomaly detection, which allows for real-time responses such as isolating a device to prevent the spread of a threat. Additionally, AI-SDN helps ensure data privacy by enforcing the correct policy in a shared network resource, which complies with data protection regulations and enhances user trust.

5.3.2. IoT

In IoT ecosystems, countless interconnected devices generate and communicate data, thus requiring an optimized and safe environment. AI-SDN brings intelligence to enhance the dynamic needs of IoT by optimizing routing, authentication, management, and energy efficiency [6].

(a) Routing optimization

Numerous interconnected IoT devices present a challenge in routing complexity as network traffic needs to travel between the nodes to its destination. By using efficient AI algorithms, optimal routing traffic prediction ensures that the routing utilizes the best path while avoiding congestion and bottlenecks. As a result, network latency experiences a reduction that leads to real-time response in critical applications, thus increasing the reliability of many IoT applications.

(b) Authentication and management

It is challenging to authenticate and manage IoT ecosystems comprising different types of devices. With the help of AI-SDN, the addition, authentication, and management of devices are easier, as the automation process can authorize and configure specific devices according to the users' needs. Additionally, AI-SDN can predict network demand based on usage trends and dynamically adjust configurations to meet the demand. The advantages of these functionalities lead to simplified device management, improved network utilization, and ensured scaling to accommodate growth in IoT.

(c) Energy efficiency

Feeding on the information provided by IoT devices, such as usage patterns, network information, and operational data, AI identifies opportunities for energy savings. Further, it can act by switching configurations to low-power modes during inactivity. The improved energy efficiency leads to lower operational costs and the environmental impact of IoT deployments, which contributes to a sustainable network operation.

5.3.3. Smart Grids/Cities

On a large scale, AI-SDN drives greater efficiency, sustainability, and resilience in smart grids and cities. The complexity of smart grids and cities may sometimes be difficult to manage, thus requiring technological advancements such as AI-SDN to manage them [54]. Here are a few ways that AI-SDN applies to smart grids and cities:

(a) Energy distribution and management

AI algorithms can monitor and predict energy demand and supply patterns using historical inputs from sensors in the grid. AI-SDN can use the information to optimize energy distribution across the grid, allowing efficient energy use while reducing costs and carbon emissions.

(b) Traffic optimization

In smart cities, traffic cameras, sensors, and connected vehicles provide valuable inputs to AI-SDN to understand traffic patterns and conditions. These elements allow dynamic traffic management that adds efficiency and optimization by providing alternative routes, adjusting traffic lights, or allocating public transportation resources in real-time. The ability to manage traffic in smart cities improves traffic flow while reducing congestion and harmful vehicle emissions.

(c) Public safety and emergency response

By integrating data from various sources, such as surveillance cameras, emergency call systems, and environmental sensors, into the network infrastructure, AI can enhance public safety by analyzing these data to detect emergencies. The advantage of having the system is a faster, more coordinated emergency response to save lives and reduce the impact of such events on public well-being.

5.3.4. Traditional Sectors

In addition to the applications of AI-SDN elaborated in previous subsections, many traditional sectors, such as finance, healthcare, and education, benefit from implementing AI-SDN. This subsection elaborates further on how AI-SDN revolutionizes these industries, transforming them to align with the technological advancements of today.

(a) AI-SDN in finance

The financial sector is a fast-paced environment where milliseconds may split between profit and loss; therefore, it requires real-time analysis and decision-making with high accuracy [55]. AI algorithms can predict market trends based on historical data, while SDN ensures low network latency for consistent connectivity with trading platforms. Additionally, vast transactions that may present fraudulent activities can be analyzed in real-time to protect sensitive data and prevent financial losses. The quick measures ensure customers' trust and improve the stability of financial institutions.

(b) AI-SDN in healthcare

AI-SDN technology helps revolutionize the healthcare sector in several ways that reduce the human workload. The breakthroughs include telemedicine, remote patient monitoring, smart health devices, and cybersecurity [56]. For example, AI processes vast amounts of medical data to provide early diagnostics to patients, speeding up hospital visits and ensuring correct diagnosis via expert consultation. Technology results in broader healthcare access and accelerates medical research to increase the potential of saving lives in time. Also, due to the nature of medical data, which is a priority to be secured, AI-SDN proactively monitors anomalies to prevent data breaches and maintain network integrity.

(c) AI-SDN in education

Schools and universities increasingly rely on digital platforms and tools; therefore, they require robust, secure, and personalized platforms to engage in learning activities. AI-SDN is a critical technology that enables educators and students to communicate and collaborate [57]. Using the AI-SDN, personal learning preferences can be analyzed to create customized educational content and adaptive learning pathways without concern about content delivery, as the network is always optimized for efficiency. It is instrumental for digital transformation in education, which provides students with quality learning resources and effective learning environments.

6. Challenges and Future of AI-SDN

The AI integration in SDN positively transforms network operations and management implementation. However, the convergence of these two technologies presents new challenges that need to be addressed to realize their full potential. By undertaking these challenges, it provides fertile ground for future research and development. This section delves into the predominant challenges in the current landscape and anticipates future directions for this domain.

(a) Accurate and timely data

The availability of accurate and timely data allows real-time decision-making for AI-SDN. The challenge lies in establishing mechanisms for quality and reliable data collection and ensuring data integrity in the face of potential network anomalies. Low-quality data leads to biased, inaccurate, or irrelevant AI outcomes, adversely affecting AI-based decision-making processes [58]. The presence of quality data reduces redundant information in data-plane measurements to save computational and networking resources.

Additionally, the complexity of features used in preprocessing algorithms can influence the computational and processing capacity of the switch. Therefore, it is important to manage the complexity to allow timely decision-making without overloading the switches [59]. For example, the current P4 switches only support a limited number of operations, which affects their ability to perform advanced data processing.

(b) Model transparency

The enigmatic nature of AI models, particularly deep learning algorithms, poses a challenge regarding interpretability and trustworthiness. Addressing the 'black box' nature of these operations will increase the model's transparency and accountability, and one example of achieving the objective is the development of explainable AI (XAI). The XAI models provide insight into each AI decision, increasing confidence in AI-driven network solutions. XAI explains the model's decisions and predictions in contrast to traditional ML approaches. However, there is still a gap in the model transparency research in SDN. Currently, there are limitations regarding the dataset, especially the real-time SDN traffic dataset for XAI models. Certain datasets, such as the UIMS and QUES [60], are confined to object-oriented programming paradigms for XAI models. As a result of the limitation, the applicability of the models in the AI-SDN landscape may be limited and lack the diversity of various network conditions. Therefore, the emphasis must be placed on broader and more diverse datasets to enhance the effectiveness and applicability of XAI in SDN.

(c) Potential vulnerability of AI models/security

While the integration of AI in SDN gives the ability to perform network decisions using intelligence, the new attack vectors that come with it may expose the system's vulnerability. Attackers might exploit AI models through techniques like model poisoning and adversarial AI, compromising network security [61]. Attackers can exploit the training dataset to reduce the performance of AI models for security detection significantly. Such degradation in performance directly affects intrusion detection mechanisms' ability to distinguish between normal and malicious data samples, leading to false negatives and false positives. Additionally, as SDN adoption becomes more widespread, it becomes an attractive target for cyber attackers to uncover zero-day vulnerabilities. Therefore, protecting AI-SDN systems from conventional and future threats is necessary to ensure reliability and integrity.

(d) Data privacy concerns

AI models require extensive data for accurate results, leading to significant privacy concerns. New approaches, such as federated learning, offer a way to preserve data as they allow distributed model training without sharing actual data [62]. However, it poses a significant challenge as distributed models require efficient coordination between various network nodes to meet the data privacy requirements. One solution to this problem is via incentive mechanisms, where data owners are rewarded for participation and high-quality contributions. The incentive mechanism must be properly designed to ensure quality participation, thus increasing the effectiveness of AI-SDN systems.

(e) Complexity of deployment

The deployment of AI-SDN solutions involves intricate software and hardware components, requiring a high level of expertise between the two fields. Additionally, modern AI-SDNs must be scalable, maintainable, and compatible with the current network infrastructure. The integration complexity of AI-SDN systems may require adaptability to solve compatibility issues between devices, such as the higher computational requirements needed to handle and analyze vast amounts of data. Various AI models deployed in AI-SDN require a flexible network that dynamically adapts to different scales and configurations. These requirements require strong knowledge in both AI and SDN fields, which are rapidly evolving, and it may be difficult to find such expertise. Therefore, there is a pressing need for a simplified deployment without diluting the functionality of AI-SDN, which may lead to the advancement of new methods. These methods or techniques may come in the form of standardization of AI-SDN interfaces, modular solutions, and enhanced tools for management purposes.

7. Conclusions

The technological convergence of AI and SDN is shaping the future of computer networking and communication. Analyzing this unification requires a bibliometric analysis to understand how the different research areas evolved during these years. It may be helpful to new researchers who wish to seek key literature, research gaps, and potential directions for future research. The analysis provides four perspectives: descriptive information, countries, authors, and content on 474 unique literatures on the WoS database from 2009 onwards. The analysis deployed various metrics to provide statistical and analytical results, uncovering relationships between authors, countries, institutions, and keywords in the literature documents. Furthermore, this study highlighted the AI-SDN taxonomy, elaborating on the domain's architecture, learning methods, and applications. Finally, this study discusses the challenges and potential for future AI-SDN convergence.

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