iJDASE International Journal of Data Analytics and Smart Education

iJDASE | ISSN: 2736-979X | Vol. 1 No. 1 (2025)
https://doi.org/10.64817/by04w168

PAPER

Academic Perspective of Data Intelligence

Sunday Adewale Olaleye[1,3], **Oluwafemi Samson Balogun**[2,3]

[1]School of Business, JAMK University of Applied Sciences, Rajakatu 35, 40100 Jyväskylä, Finland

[2]School of Computing, University of Eastern, FI-70211. Finland

[3]Centre for Multidisciplinary research and Innovation (CEMRI), Finland

sunday.olaleye@jamk.fi
samsb@uef.fi

ABSTRACT

This study focuses on the academic opinion about data intelligence, understood and described through its main trends, productive authors, the most influential journals, and collaborative networks. Data was collected from two major scientific databases, Web of Science and Scopus, covering all publications from 1994 to 2023, using the Biblioshiny app to manage this analysis and find out the conceptual, intellectual, and social structures related to the research about data intelligence. The results reflect the field has growing interests, with crucial contributions from various countries and institutions. However, issues like data quality, competency gaps, or ethical concerns exist. These findings conclude some ideas for further research that would solve the indicated limitations and maximize the potential of data intelligence.

KEYWORDS

Data Intelligence, Data Quality, Bibliometric Analysis, Machine Learning, Research Trends

1 INTRODUCTION

In the age of the digital revolution, data intelligence has emerged as a transformative force across multiple domains, from business and healthcare to government and academia. The unprecedented explosion of data, often called 'big data', presents opportunities and challenges. According to the International Data Corporation (IDC), the global data

Sunday Adewale Olaleye, Oluwafemi Samson Balogun. (2025). Academic Perspectives of Data Intelligence. *International Journal of Data Analytics and Smart Education (iJDASE),* 1(1) pp. 1-24
https://doi.org/10.64817/by04w168

Article submitted: 12.02.2025 Revision uploaded: 12.02.2025 Final Acceptance: 13.02.2025

sphere is expected to grow to 175 zettabytes by 2025, highlighting the scale at which data is being generated and its potential for insights and innovation [1]. This burgeoning data expanse necessitates sophisticated collection, analysis, and interpretation methods, forming the crux of data intelligence.

Data intelligence refers to the comprehensive process of analyzing and interpreting various forms of data to guide decision-making, enhance efficiencies, and predict trends. An example is how data intelligence shapes public sector service delivery and local needs [2]. It encapsulates techniques from data mining, machine learning, and artificial intelligence to transform raw data into meaningful and actionable insights. The significance of data intelligence lies in its capability to process vast amounts of information and its potential to drive strategic initiatives and innovations across sectors. For instance, in healthcare, data intelligence is pivotal in predictive analytics for patient outcomes, personalized medicine, and operational efficiency [3].

Despite its transformative potential, the field of data intelligence faces significant challenges and gaps. One prominent gap is the issue of data quality and reliability. Many organizations need help with complete, consistent, or outdated data, which can undermine the effectiveness of data intelligence processes. Additionally, there needs to be more skilled professionals adept in advanced data analytics and machine learning techniques, posing a bottleneck to fully utilizing data intelligence capabilities. Furthermore, ethical and privacy concerns regarding data collection and usage remain contentious, necessitating robust frameworks and policies to safeguard against misuse.

In the contemporary era marked by rapid technological advancements and environmental challenges, the significance of data intelligence cannot be overstated. This field has emerged as a cornerstone in addressing complex problems across various domains, including climate change, urban planning, healthcare, and industrial management. A noticeable increase in drought frequency and severity has been observed globally due to climate change, prompting scientists to develop drought prediction models for mitigating impacts. Droughts are typically monitored using drought indices (D.I.s), the most probabilistic, highly stochastic, and nonlinear [4]. This paper explores the academic perspectives on data intelligence, illustrating its importance, methodologies, and inherent challenges.

Data intelligence refers to the comprehensive process of analyzing and interpreting various forms of data to guide decision-making, enhance efficiencies, and predict trends. The International Data Corporation (IDC) anticipates that the global data sphere will expand to 175 zettabytes by 2025, emphasizing the vast amount of data generated and its potential for insights and innovation [1]. The importance of data intelligence lies in its ability to process vast amounts of information and drive strategic initiatives and innovations across sectors. For instance, data intelligence is crucial in predictive analytics for patient outcomes, personalized medicine, and operational efficiency in healthcare. Similarly, digital transformation in urban planning enhances efficient, place-based, and bottom-up innovation policies at different spatial scales as digital technologies modify existing policy-design routines in cities and regions [5].

Despite its transformative potential, data intelligence faces significant challenges and gaps. One prominent gap is the issue of data quality and reliability. Organizations often need help with complete, consistent, and updated data, which can undermine the effectiveness of data intelligence processes. Additionally, there needs to be more skilled professionals adept in advanced data analytics and machine learning techniques, posing a bottleneck to fully utilizing data intelligence capabilities. Furthermore, ethical and privacy concerns regarding data collection and usage remain contentious, necessitating robust frameworks and policies to safeguard against misuse. The need for accurate drought prediction models exemplifies this challenge, as droughts are natural hazards with highly stochastic and nonlinear characteristics influenced by several climatic variables [6].

The existing studies used forecasting and prediction intelligently with data [4,7]. Another study dwells on data intelligence for digitalizing e-healthcare services [3]. A further study explored intelligent data for Decision-Support Systems [6], while Panori et al. [5] explored the related challenges in deploying digital platforms. The longitudinal study gaps in the existing literature motivate this study.

The primary objective of this study is to explore the academic perspectives on data intelligence, highlighting its significance, methodologies, and inherent challenges. The study will address the following research questions to achieve this objective: (a) What is the volume of publications within the field of data intelligence over a defined period to identify trends and patterns in research output? (b) Who are the most prolific and influential authors, institutions, and countries contributing to the data intelligence field based on quality and quantity metrics? (c) How do we understand the networks, patterns, and impact of authors and institutions within the academic community of data intelligence? (d) What are the revealed collaboration networks among researchers, institutions, and countries? How do we identify major research clusters and understand the dynamics of research collaboration? (e) What are the identified emerging trends and hot topics within the field of data intelligence, pinpointing rapid development and interest areas?

Studying the academic perspectives of data intelligence is crucial for understanding its significance, addressing gaps in the literature, and maximizing its potential benefits. This study analyses the key trends, authors, journals, and institutions in data intelligence through bibliometric data analysis. Additionally, it will examine the ethical considerations associated with data intelligence. The study sections, from methodology to conclusion, will provide a comprehensive analysis of the academic perspectives of data intelligence.

2 METHODOLOGY

This section outlines the methodology for conducting a bibliometric analysis of the field of "Data Intelligence." The primary objective is to explore the field's conceptual, intellectual, and social structures. The analysis utilized Web of Science and Scopus data collected on September 1, 2023.

2.1 Data Collection

Data for this study were sourced from two major academic databases: Web of Science and Scopus. The search strategy employed the keyword "Data Intelligence" in the topic field. Boolean operators and filters were used to refine the search, limiting results to English articles from 1994, 2004, 2006, 2007, 2008, 2009, 2011, 2014, 2016, 2017, 2018, 2019, 2020, 2021, 2022, and 2023. The study period spans from 1994 to 2023 and focuses exclusively on articles. The Data Intelligence PRISMA chart documents detailed inclusion and exclusion criteria.

2.2 Data Cleaning

Data cleaning involved merging Web of Science and Scopus datasets using R-Studio. Initially, 143 articles were retrieved from the Web of Science and 172 from Scopus. After removing 130 duplicate entries, the final dataset comprised 185 unique articles.

2.3 Data Analysis and Visualization

The primary data analysis and visualization tool was the Biblioshiny app, a web-based application for bibliometric analysis. The analysis focused on three key bibliometric indicators: conceptual structure, intellectual structure, and social structure.

2.4 Bibliometric Research Design

This study adopted a quantitative methodology, following the six steps of the bibliographic workflow outlined by Olaleye [8]; Olaleye, Balogun & Adusei-Mensah [9], and Agjei et al. [10]:

Formulation of Research Questions: Five unique research questions were designed to guide the study.

Data Source Selection: Web of Science and Scopus were identified as the most appropriate databases for data collection. Bibliographic data were searched, filtered, and exported.

Data Analysis: Bibliometric data analysis was conducted using the Biblioshiny app [11].

Data Visualization: The Biblioshiny app was also used to visualize data intelligence research.

Results Presentation: Results generated from Biblioshiny were presented and interpreted.

Conclusion: The study concluded with a summary of findings, a discussion of limitations, and suggestions for future research.

2.5 Validation Techniques

Several validation techniques were employed to ensure the validity and reliability of the results. These included cross-referencing Web of Science and Scopus data and employing robust data-cleaning methods to eliminate duplicates and errors.

2.6 Ethical Standards

The study adhered to ethical standards in data handling and reporting. All data collected and analyzed were from accessible academic databases, ensuring compliance with relevant guidelines and regulations.

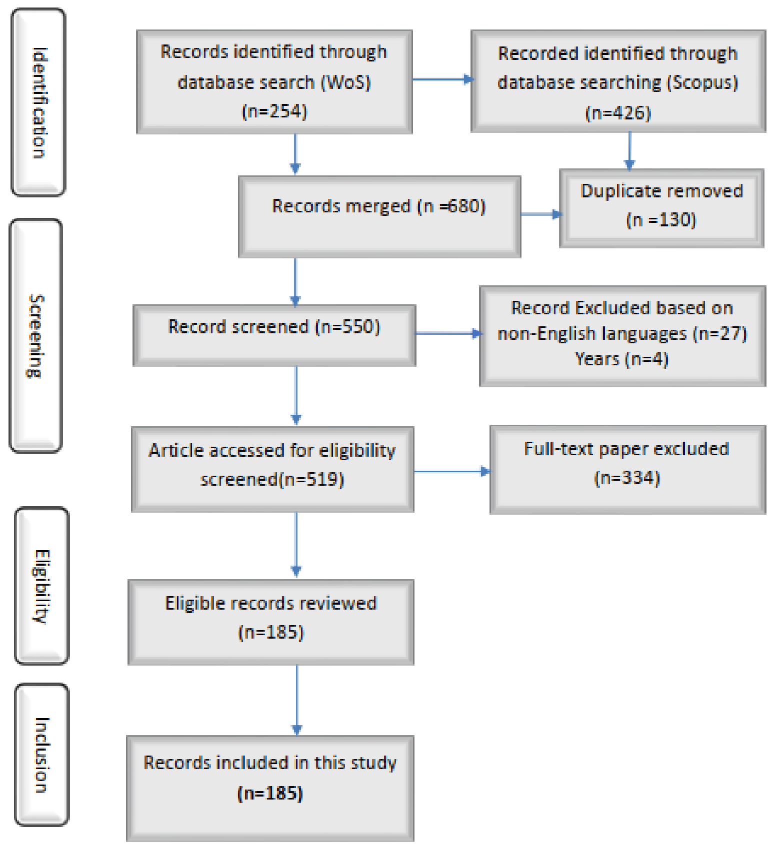

Fig. 1: Data Intelligence PRISMA

Fig. 2: Data Intelligence Academic Literature Descriptive Statistics

3 RESULTS

This section provides the findings of the quantitative bibliometric analysis. The research questions the study answers determine how the results are presented. These questions seek to offer readers a comprehensive picture of the research emphasis.

4.1. Q1. How has data intelligence research progressed over time?

This study performed two studies examining the annual scientific production and citation rate every year to assess the advancements made in understanding the research landscape of data intelligence. These quantitative evaluations offer precise data on the field's performance and provide insight into prospects. The primary research topic of this study aims to examine the historical and projected trends in data intelligence research.

4.1.1. Annual scientific production

According to the information presented in Figure 3, our dataset indicates that the yearly scientific output of research papers on data intelligence began in 1994, with a single article published that year. Between 1994 and 2023, 185 publications have been released from various sources. According to Figure 3, there was a consistent increase in the production of articles from 1994 to 2023. However, there was a growing interest in data intelligence starting in 2014, while a significant expansion was observed in 2019. Regarding scientific article production, 2022, 2021, and 2019 were the most productive, with 46, 37, and 28 documents, respectively.

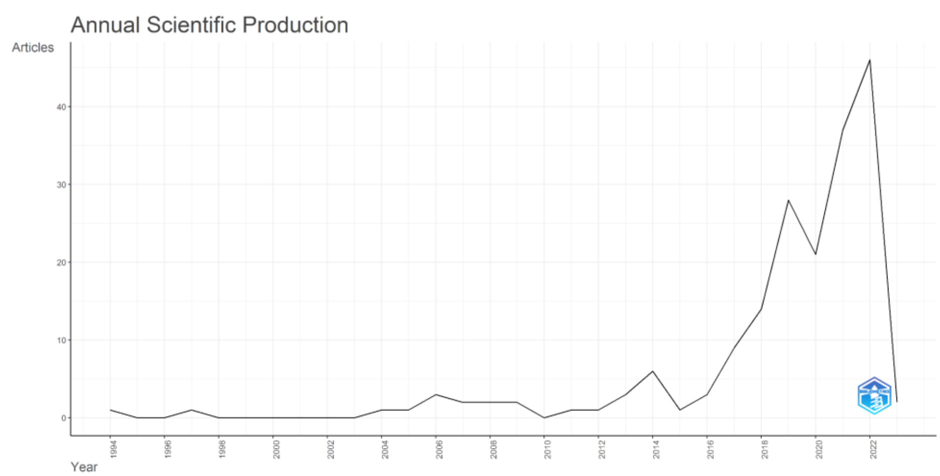

Fig. 3: Data Intelligence Scientific Production

In 2016, there were three publications with a total citation mean of 14.88, the most recorded. These publications had eight citable years. The second highest mean of 6.65 was recorded in 2007, with two papers totaling seventeen years. In 2019, there were 28 documents with a mean of 6.16, totaling five citable years. Conversely, the lowest average total citation per year was zero (0) for five specific years: 1994, 1997, 2004, 2009, and 2023. In 2022, 46 articles had an average annual citation count of 1.17. This finding suggests that the number of scientific papers did not necessarily correlate with increased citations. The citation is contingent upon the papers' calibre and availability for individuals who require them for scholarly endeavours (Figure 4).

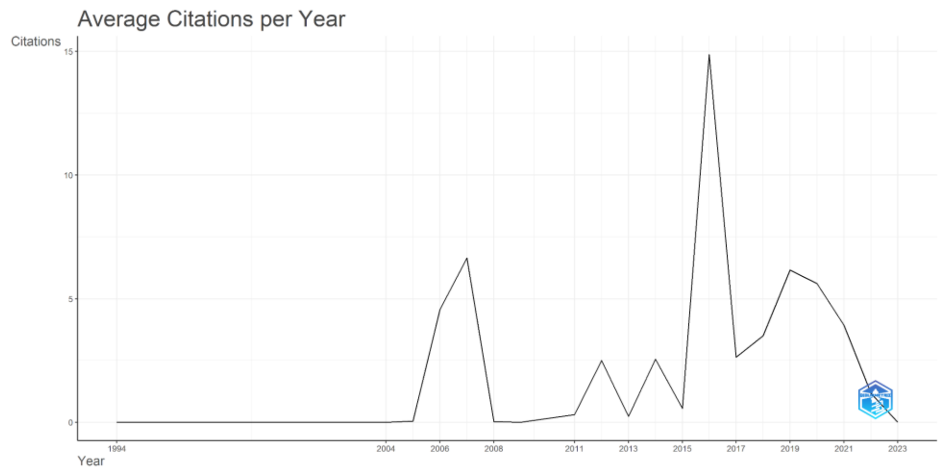

Fig. 4: Data Intelligence Average Citations Per Year

4.2. Q2. who are the most relevant authors publishing in data intelligence research?

Fig. 5 provides a supplementary analysis by presenting a summary of the top ten (10) authors in the field of data intelligence from 1994 to 2023. In Figure 4, the increased diameter of a circle corresponds to a higher number of documents released annually by the author. Furthermore, the intensity of the circle's shade directly correlates with the number of citations it received in that particular year. The count of output years for an author starts from the year they publish their initial publication. Consequently, the writers' total production years differ. Al-Ansari N began publishing data intelligence in 2019 and has four years of experience. Based on this comprehension, it can be inferred that Yaseen Z is the most prolific author, followed by Ma J and Sun Y, each with thirteen papers. Furthermore, the analysis reveals that Li W., Mao Y., Salih S., Tang L., and Zhou G. are the third most productive authors making significant contributions to data intelligence. This study was analyzed by the authors from two viewpoints, namely the number of documents per author and the number of citations per author, to analyze the prolific authors in the field of data intelligence and assess their relevance. Fig. 6 displays the top 10 writers in the subject based on the number of papers they have published. Yaseen Z is the author with the highest number of publications. Yaseen has published twenty-six documents in the field of data intelligence. Ma J. and Sun Y. are the other authors who have also contributed to this field, each having thirteen documents published. Yaseen's output in data intelligence was twice as high as that of the author's closest competitors. Yaseen's twenty-six publication pieces demonstrate the author's contributions to several published papers.

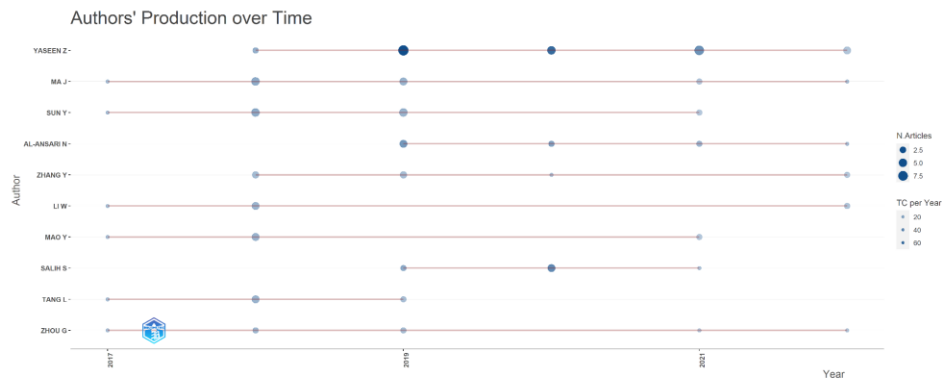

Fig. 5: Data Intelligence Authors' Production over Time

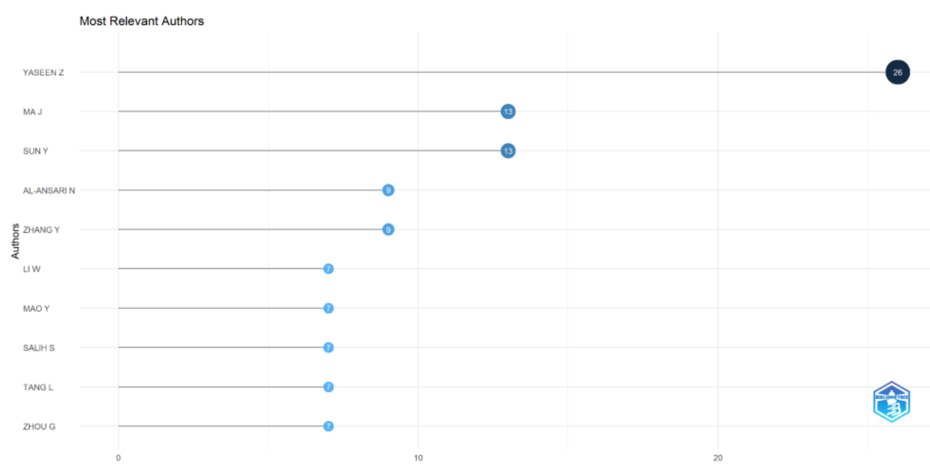

Fig. 6: Data Intelligence Most Relevant Authors

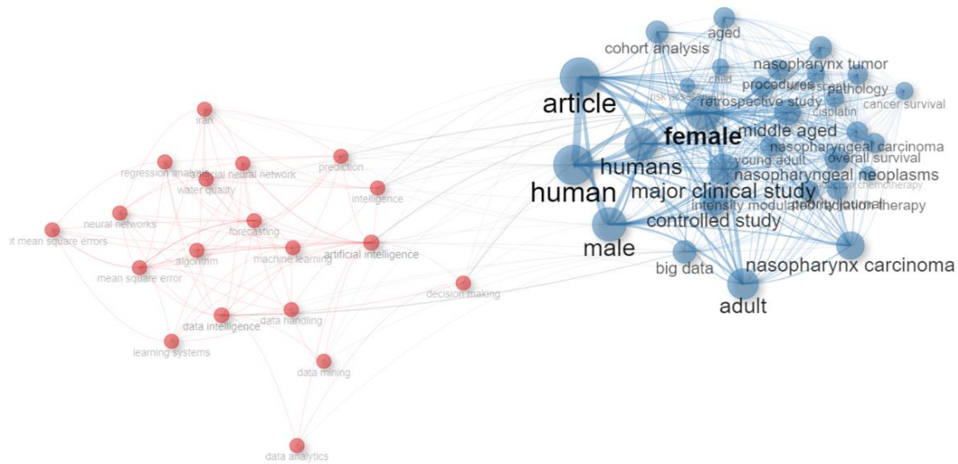

Fig. 7: **Data Intelligence Co-occurrence Keywords Network**

Factorial analysis aims to map a framework's conceptual structure using word cooccurrences in a bibliography. This analysis can use dimensionality reduction techniques like MDS, CA, or MCA. This study shows two clusters of documents that reveal some familiar concepts. Figure 7 shows the conceptual structure map of research papers in data intelligence published between 1994 and 2023. Creating it involved using factorial analysis to examine numerous keyword correspondences. The following two clusters emerged: blue and red. The blue cluster has nineteen topics of data intelligence that dwell on regression, neural network, prediction, artificial intelligence, decision making, mean square error, learning systems, data mining, data analytics, machine learning, algorithms, forecasting, and intelligence, while the red cluster has thirty topics of data intelligence that include cohort, article, human, male, big data, adult, aged, nasopharyngeal, nasopharynx, tumour, cancer survival, pathology, carcinoma, overall survival, neoplasms, controlled study, and female.

The partnership between countries highlights the collaborations among prolific writers in web intelligence. Iran and Iraq have the highest collaboration, with two articles. The remaining pairs (Australia and Malaysia), (Australia and Poland), (Iran and Australia), (Iran and Malaysia), (Iran and South Africa), (Iran and Vietnam) and a lot more have one each. Given that some of these countries are among the top producers of web intelligence research, their collaborations are not surprising (see Figure 8).

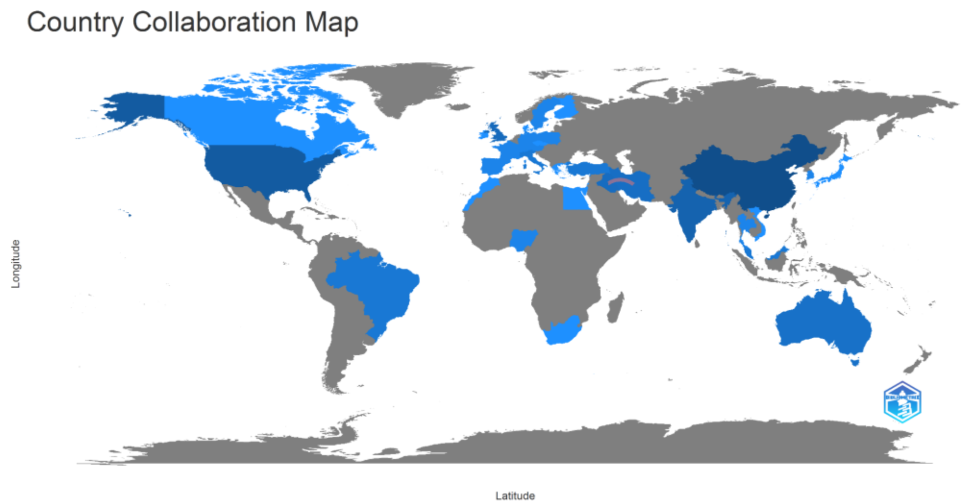

Fig. 8: Data Intelligence Country Collaboration Map

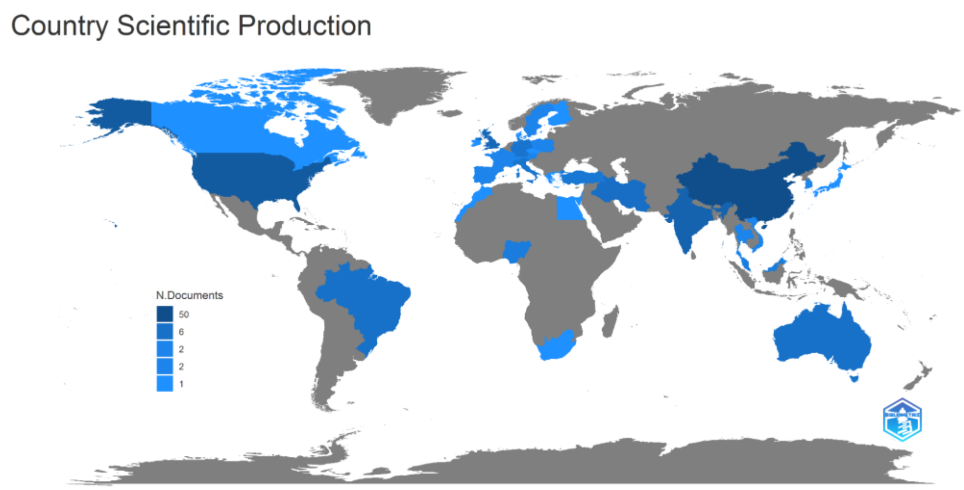

Fig. 9: Data Intelligence Country Scientific Production

Figure 9 reveals that research on data intelligence has been actively investigated in 35 different nations. China is at the forefront of scientific production in data intelligence research, having published 50 papers demonstrating its substantial contribution. The United States (23), India (14), the United Kingdom (10), Iran and Iraq (7), Australia and Brazil (6), Germany and Italy (5), and Turkey (4) are the other countries that are at the forefront of data intelligence research. Out of the 161 articles, the top 10 nations contribute to 76.4% of them, indicating that most research production is centred in Asia, North America, and Europe. Countries like the USA, India, Germany, Australia, Italy, and the U.K., which are considered developed, have a significant influence.

On the other hand, smaller countries like Finland and South Africa also actively contribute. The extensive range of countries engaged in data intelligence research indicates a collective and widespread interest. The results emphasize the significance global cooperation, research facilities, and financial assistance in promoting the progress of data intelligence research.

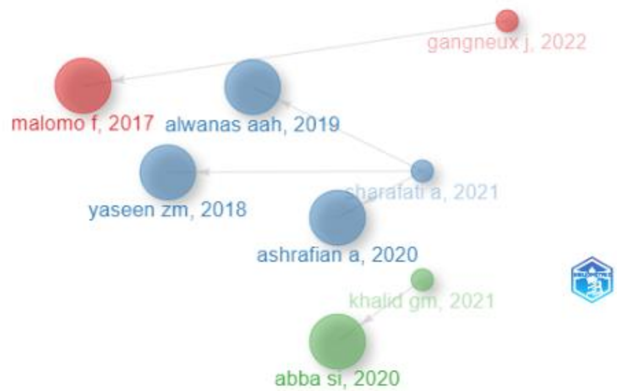

Fig. 10: **Data Intelligence Historiograph**

3.1 Historiograph

A historiograph is a visual tool that depicts the chronological development and historical progression of a specific field of study, research topic, or scientific discipline. It shows the relationships between key publications, authors, and their contributions over time, highlighting the evolution and influence of ideas and knowledge. Several authors had commonalities in their research titles, keywords, and keyword Plus: Malomo, I. (2017) in Policy Internet, Gangneux, J. (2022) in Data Policy, Yaseen, Z. M. (2018) in J. Hydrol., Alwana, A. A. H. (2019) in Engineering Structure, Ashrafian, A. (2020) in Construction Build Mater., Sharafati, A. (2021) in Front Struct. Civil Engineering, Abba, S.I. (2020) in Journal of Water Process Engineering, and Khalid, G.M. (2021) in Futur. J. Pharm. Sci. The years 2020 and 2021 were notable, with two authors publishing in each (Figure 10).

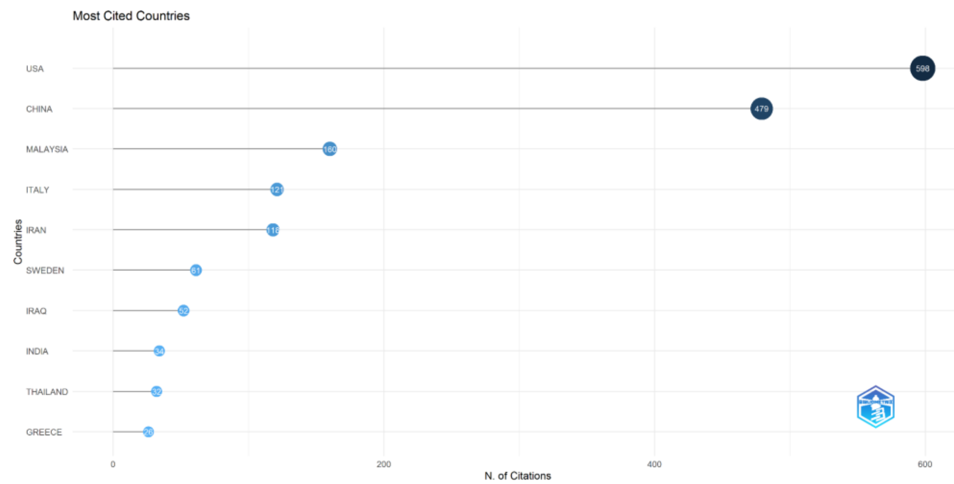

Fig. 11: Data Intelligence Most Cited Countries

3.2 Most Cited Countries

According to Figure 11, the USA is the most frequently mentioned country in data intelligence between 1994 and 2023, with 508 citations. China is the second most referenced country, with 479 citations, followed by Malaysia, with 180 citations. The USA's dominance in data intelligence validates its status as a reliable nation that embraces developing technologies. Furthermore, the USA has been at the forefront of countries that have successfully attained the data intelligence objectives set by the United Nations. Although the USA has achieved this, it strives to enhance data intelligence dissemination further.

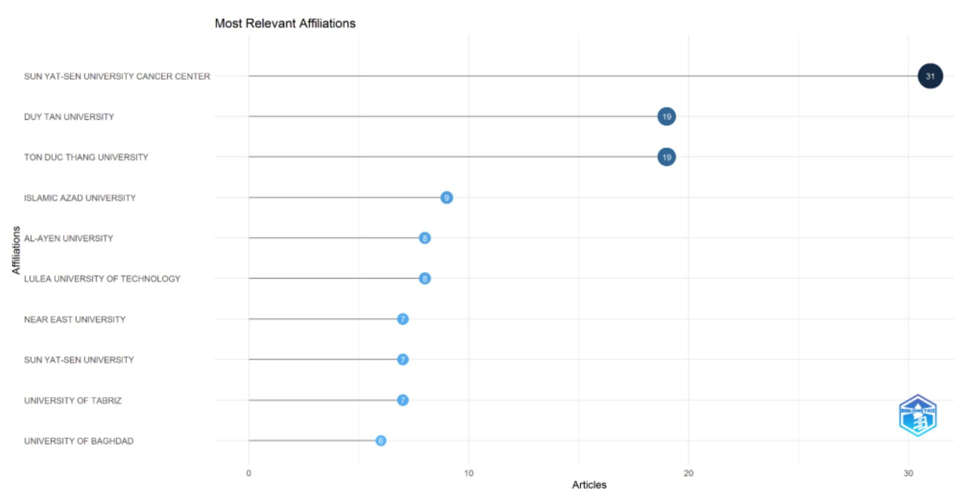

Fig. 12: Data Intelligence Most Relevant Affiliation

3.3 Most Relevant Affiliation

Based on the statistics shown in Figure 12, the top five universities in the field of data intelligence are the Sun Yat-Sen University Cancer Centre with 31 publications, Duy Tan University and Tonne Duc Thang University with 19 articles each, Islamic Azad University with nine articles, and Al-Ayen University with eight papers. Unsurprisingly, the Sun Yat-Sen University Cancer Centre took the lead in the relevant affiliation. The authors affiliated with the University have been actively involved in projects related to data intelligence.

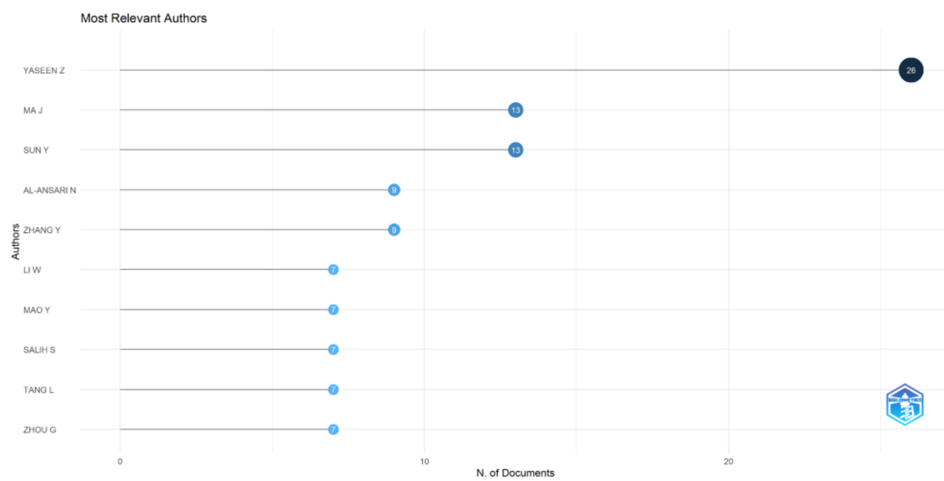

Fig. 13: **Data Intelligence Most Relevant Authors**

3.4 Relevant Authors

Figure 13 provides a supplementary study by presenting a summary of the top ten authors in the field of data intelligence from 1994 to 2023. In Figure 12, the circle size corresponds to the number of documents released annually by the author. Furthermore, the intensity of the circle's darkness corresponds directly to the magnitude of citations obtained during that particular year. The count of output years for an author starts from the year they publish their initial publication. Consequently, the writers' total production years differ. Based on this understanding, it is clear that Yassen Z is the most prolific author, with Ma J and Sun Y coming in second with thirteen papers each. Furthermore, the analysis reveals that Al-Ansari N and Zhang Y are positioned as the third most productive authors on data intelligence, with each having a combined total of nine publications. Out of the ten highly productive authors, the other five had seven articles, as indicated in Figure 13.

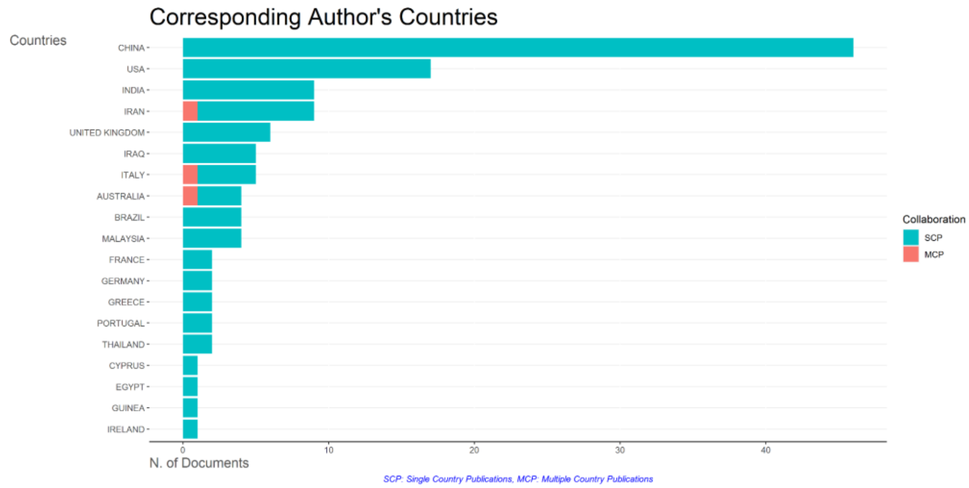

Fig. 14: **Data Intelligence Corresponding Author's Countries**

3.5 Countries of the Corresponding Authors

Figure 14 categorizes the key contributors to "Global Data Intelligence Research" into single-country and multiple-country publications (MCP). In single-country publication (SCP), a document is defined as having all its authors originating from the same nation. On the other hand, Multi-Country publication (MCP) refers to the number of documents with at least one co-author from a different country.

Typically, it quantifies how much a country engages in international cooperation. China is first on the SCP list with 46 papers, while the U.S. follows with 390 articles. Iran and Iraq have nine articles suggesting that academics from both nations have made noteworthy contributions to the area through collaborations and publications in their own countries. China continues to dominate the MCP (46) list, with the USA (17), India (9), and Iran (8) also making notable contributions through multi-country publications.

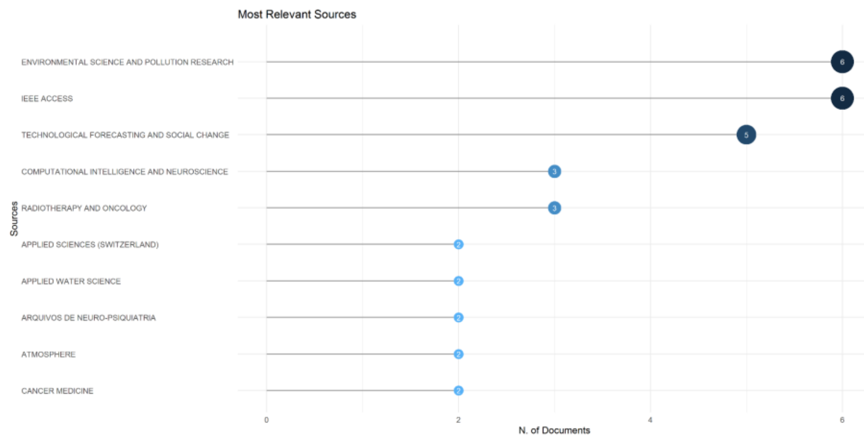

Fig. 15: Data Intelligence Most Relevant Sources

3.3 Relevant Sources

Figure 15 displays a concise overview of the ten most influential sources in the field of data intelligence, spanning from 1994 to 2023. Figure 13 depicts a correlation between the size of a circle and the number of documents the sources release annually. Moreover, the circle's darkness level is directly proportional to the number of citations obtained in that specific year. The number of years of journal production is evident in this study. According to this result, it is evident that Environmental Science and Pollution Research and IEEE Access are the most productive sources, followed by Technological Forecasting and Social Change with five papers, and Computational Intelligence and Neuroscience and Radiotherapy and Oncology with three papers each, ranking third.

Moreover, the analysis indicates that Applied Sciences (Switzerland), Applied Water Science, Arquivos De Neuro-Psiquiatria, Atmosphere, and Cancer Medicine are ranked as the least productive authors in data intelligence. Each of these authors has only published two papers. Among the ten highly productive authors, the remaining five contributed two publications, as depicted in Figure 13.

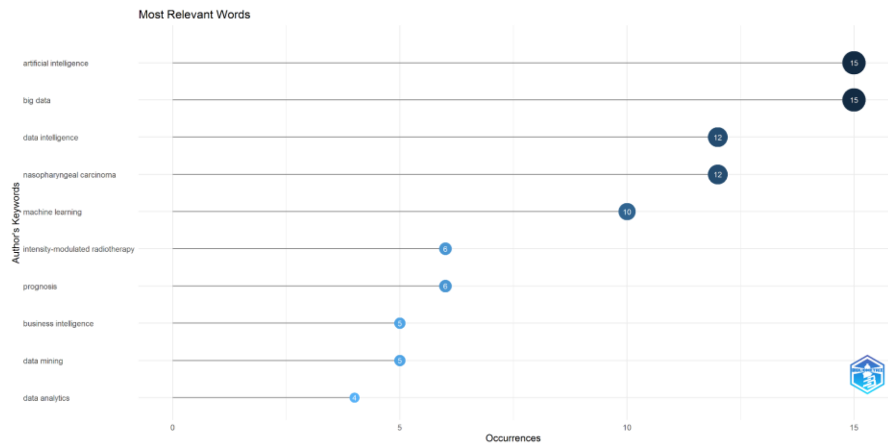

Fig. 16: Data Intelligence Most Relevant Words

Artificial intelligence and extensive data are the most relevant words in the data intelligence study, appearing fifteen times each. Data intelligence and nasopharyngeal carcinoma appear twelve times each, following the most relevant words. This figure illustrates the relevant words in data intelligence research. The third most significant word is "machine learning," which appears eleven times throughout the sentence. The term "data analytics" appeared four times, making it the least often used keyword in research on data intelligence (Figure 16).

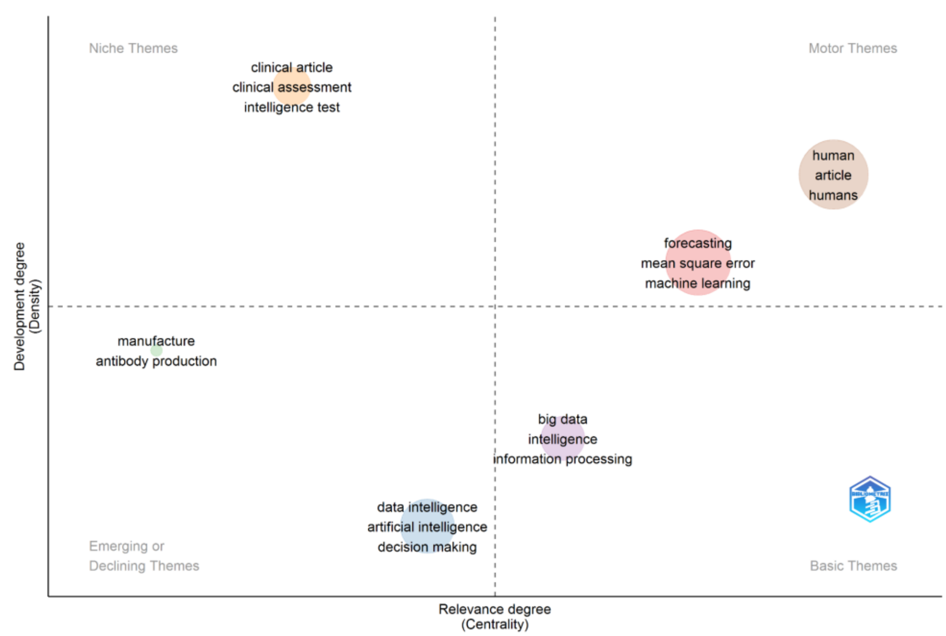

Fig. 17: Data Intelligence Thematic Map

Figure 17 depicts the thematic map of the web intelligence field using four quadrants: the upper right quadrant (Q1), the upper left quadrant (Q2), the lower left quadrant (Q3), and the lower right quadrant (Q4). In web intelligence production, Q1 represents the "driving themes," which include topics like the human, article, humans, forecasting, mean square error and machine learning. Q2 signifies the "highly specialized themes," such as clinical articles, clinical assessments, and intelligence tests. Q3 indicates the "emerging or disappearing themes," including manufacturing, antibody production, data intelligence, artificial intelligence, and decision-making. Q4 represents the "foundational themes," such as big data, intelligence, and information processing.

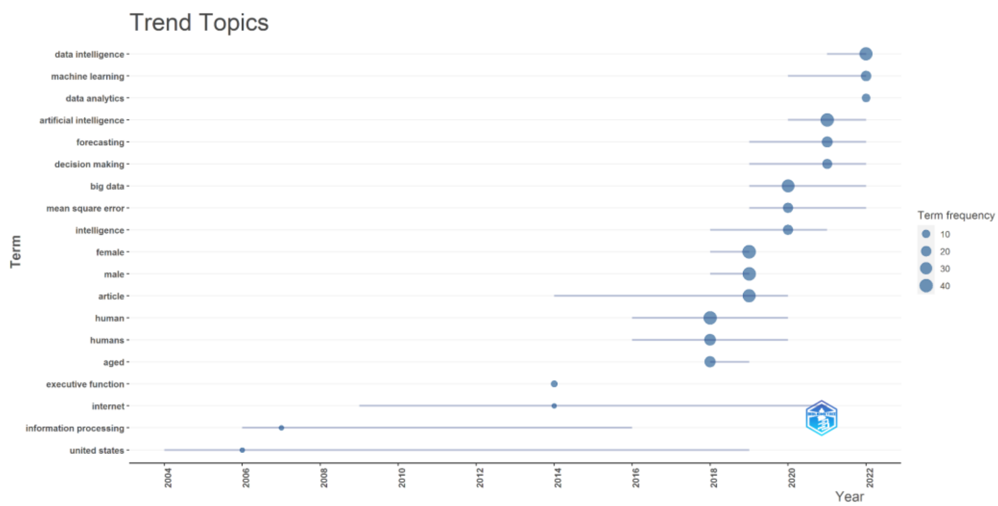

Fig. 18: Data Intelligence Trend Topics

3.3 Trend Topics

Based on the author's keywords from our dataset, Figure 18 gives an overview of the trending topics in the scientific production of research publications in data intelligence for the period (1994 to 2023). Further, the topics are presented in a hierarchical arrangement each year. For instance, in 2021, artificial intelligence and forecasting were trending topics. In 2022, data intelligence, machine learning, and data analytics were trending. It is exciting that some trending topics with higher frequency were predominant between 2018 and 2019 but have yet to extend to 2022.

An example is artificial intelligence, with 39 frequencies and trends between 2020 and 2022, and data intelligence, with a trend between 2021 and 2022 with 38 frequencies. Likewise, forecasting trends between 2019 to 2022 had 20 frequencies.

4 FINDINGS

The concepts associated with machine learning (ML), data intelligence (DI), artificial intelligence (A.I.), decision-making, forecasting, and big data are increasingly intertwined in this fast-changing digital technology and information management environment. These domains inform and influence one another and shape the way organizations and people move through the labyrinth of a modern digital world.

Machine learning is a sub-branch in artificial intelligence that deals with developing algorithms and statistical models that enable the systems concerned to optimally perform specific tasks without being explicitly programmed [12]. Another dimension, data intelligence, is making valuable insights or actionable knowledge from large, complex datasets [13]. To that respect, the overlap between machine learning and data intelligence is that the former algorithms are heavily used to analyze and interpret information data to discover patterns of behaviour, trends, or relationships that become informants during decision-making.

Cui et al. [14] establishes that the relationship between ML and DI is synergistic since machine learning models can leverage data intelligence, incorporating predictive analytics, anomaly detection, and personalized recommendations. In contrast, current technological innovations in data collection, storage, and processing have driven efforts to develop advanced ML models able to cope with augmented volumes, velocities, and varieties of data.

Artificial intelligence is a broader term encompassing machine learning. It focuses on developing systems that perform tasks typically associated with human intelligence, such as problem-solving, reasoning, and learning. The overlap between A.I. and decisionmaking arises precisely from the possibility of AI-enabled systems aiding and complementing human decision-making processes.

Recent research, such as Agrawal et al. [15], has examined how AI-based tools can extend and complement the decision-making process with predictive analytics, scenario analysis, and decision support. Again, tempering its full integration with human decision-making processes, Kaplan and Haenlein continue to outline how A.I. is integrated into the human decision-making process while retaining the oversight and accountability of humans.

Forecasting, which involves estimating future events or trends using historical data and analytical techniques, has become more dependent on insights gained from big data in recent years. Big data denotes large, complex, and incredibly fast-growing datasets that require special processing to store, manage, and analyze.

Big data, however, feeds into this need for advanced forecasting models with accuracy and granularity; simultaneously, the insights from such models can also talk about extensive data collection and management as Kambatla et al. [16] pointed out in 2014, the work by Davenport & Patil [17] demonstrates how leveraging big data analytics improves demand forecasting and further enhances supply chain optimization.

Machine learning, data intelligence, artificial intelligence, decision-making, forecasting, and big data carry profound interrelationships and interdependencies. Machine learning and data intelligence aim to bring valuable insights from large datasets. Artificial intelligence and decision-making work based on these extracted insights to give meaning and enhance a means for informed decision-making. The ability of the former to predict future events or trends is paramount in forecasting.

These connections, therefore, involve far-reaching implications as organizations and individuals strive to capture the power of these technologies in pursuit of innovation, efficiency, and informed decisions. For instance, integrating these topics has grown increasingly popular in predictive maintenance, personalized marketing, and smart city planning [18-19].

5 LIMITATIONS AND FUTURE RESEARCH

Though data intelligence holds huge potential for transformation, there are also quite formidable challenges and gaps. One of the prominent gaps is the quality and reliability of the data. Not many organizations have complete, consistent, and up-to-date data that can support data intelligence processes effectively. Next is the need for more professionals with deep knowledge of advanced data analytics and machine learning techniques, which is emerging as a bottleneck in fully tapping the potential of data intelligence. Furthermore, ethical concerns and privacy related to data collection and usage are very contentious and thus require robust frameworks and policies to prevent misuse.

Future studies need to address these limitations, focusing on the following:

Data Quality Improvement: Future studies should advice on developing methods and tools to enhance data quality.

Skill Creation: Future studies should come up with education programs and training that build expertise in cutting-edge data analytics and machine learning.
Ethical Frameworks: Future studies should establish comprehensive ethical guidelines and privacy protection measures to address concerns related to data use.
Application-Specific Research: Future studies should diversify into using data intelligence in fields like healthcare, finance, and environmental science are fundamental to recognizing unique problems and solutions.
Interdisciplinary Collaboration: Future studies should facilitate the collaboration of data scientists with domain experts to drive interdisciplinary insights for better outcomes in data intelligence.

6 CONCLUSION

The paper comprehensively reviews the academic perspectives on data intelligence, undertaking a bibliometric analysis between 1994 and 2023. It shows how this area evolved, key trends, prolific authors, influential journals, and collaborative networks. There is increasing interest and essential developments in data intelligence research, with notable contributions from diverse countries and institutions. While useful, more is required to handle data quality, skill shortages, and ethical concerns if the full potential of data intelligence is to be delivered. This situation implies that future research should focus on enhancing data quality, developing expertise, and setting up ethical frameworks. It challenges specific applications to keep them moving forward.

7 REFERENCES

1. Woodie, Alex (2018). "Global DataSphere to Hit 175 Zettabytes by 2025, IDC Says". From https://www.datanami.com/2018/11/27/global-datasphere-to-hit-175-zettabytes-by-2025-idc-says/. Access 02.07.2024.
2. Malomo, F., & Sena, V. (2017). Data intelligence for local government? Assessing the benefits and barriers to use of big data in the public sector. *Policy & Internet*, 9(1), 7-27.
3. Sangaiah, A. K., Rezaei, S., Javadpour, A., & Zhang, W. (2023). Explainable A.I. in big data intelligence of community detection for digitalization e-healthcare services. *Applied Soft Computing*, 136, 110119.
4. Yaseen, Z. M., Ali, M., Sharafati, A., Al-Ansari, N., & Shahid, S. (2021). Forecasting standardized precipitation index using data intelligence models: regional investigation of Bangladesh. *Scientific reports*, 11(1), 3435.
5. Panori, A., Kakderi, C., Komninos, N., Fellnhofer, K., Reid, A., & Mora, L. (2021). Smart systems of innovation for smart places: Challenges in deploying digital platforms for co-creation and data-intelligence. *Land Use Policy*, 111, 104631.
6. Yaseen, Z. M., & Shahid, S. (2021). Drought index prediction using data intelligent analytic models: a review. Intelligent Data Analytics for Decision-Support Systems in Hazard Mitigation: Theory and Practice of Hazard Mitigation, 1-27.
7. Egbueri, J. C. (2022). Predicting and analyzing the quality of water resources for industrial purposes using integrated data-intelligent algorithms. Groundwater for Sustainable Development, 18, 100794.
8. Olaleye, S.A. Visualizing cultural emotional intelligence literature: a bibliometric review 2001– 2020. In:Laine, P., Némethová, I., Wiwczaroski, T. (eds.) Inter-cultural Competence at Work. Seinäjoki: Seinäjoen ammattikorkeakoulu. Publications of Seinäjoki University of Applied Sciences B. Reports, 2020: 160, pp. 142–156.https://urn.fi/URN:NBN:fi-fe20201215100768.
9. Olaleye, S. A., Balogun, O. S., & Adusei-Mensah, F. (2023). Bibliometric structured review of tuberculosis in Nigeria. *African Health Sciences*, *23*(2), 139-60.
10. Agjei, R. O., Adusei-Mensah, F., Balogun, O. S., & Olaleye, S. A. (2023). The Bibliometric Global Overview of COVID-19 Vaccination. In *International Conference on Intelligent Systems Design and Applications* (pp. 287-298). Springer, Cham.
11. Olaleye, S., Olaleye, E., Balogun, M., & Balogun, O. (2023). Global spotlight of students and teachers wellbeing. A bibliometric viewpoint.

15th International Conference on Education and New Learning Technologies, Palma, Mallorca, Spain, 3658 – 3666.

12. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.
13. Russom, P. (2011). Big data analytics. TDWI best practices report, fourth quarter, 19(4), 1-34.
14. Cui, Z., Ke, R., Pu, Z., & Wang, Y. (2021). Deep learning for image-based traffic data analytics: A survey. Transportation Research Part C: Emerging Technologies, 124, 103-116.
15. Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction machines: The simple economics of artificial intelligence. Harvard Business Review Press.
16. Kambatla, K., Kollias, G., Kumar, V., & Grama, A. (2014). Trends in big data analytics. Journal of Parallel and Distributed Computing, 74(7), 2561-2573.
17. Davenport, T. H., & Patil, D. J. (2012). Data scientist: The sexiest job of the 21st century. Harvard Business Review, 90(10), 70-76.
18. Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of machine intelligence. California Management Review, 61(4), 5-14.
19. Mishra, N., Lin, H. C., & Chang, H. T. (2017). A cognitive adopted framework for IoT big-data management and knowledge discovery prospective. International Journal of Distributed Sensor Networks, 13(9), 1-13.

8 AUTHORS

Sunday Adewale Olaleye is a Senior Lecturer at Jamk University of Applied Sciences, Finland got his Doctor of Science (D.Sc.) in Marketing from the University of Oulu, Oulu Business School (AACSB), Finland. He received his Master of Science in Information Systems from Abo Akademi University, Turku, Finland; his MBA from the Lapland University of Applied Sciences, Tornio, Finland; his NMS iICT Certificate, Innovation, and Entrepreneurship from the Nordic Master School of Innovative ICT, Turku Centre for Computer Science (TUCS), Turku, Finland; and his Certificate of Leadership and Management in Health from the University of Washington, USA. He had his postdoctoral studies at the University of Oulu in Finland, and he is a visiting professor at the Universidad de las Américas Puebla (UDLAP) in Mexico. He has presented papers at conferences and published them in academic journals.

Oluwafemi Samson Balogun is a former lecturer at the Department of Statistics and Operations Research, Modibbo Adama University of Technology, Yola, Adamawa State, Nigeria. He is an International Visiting Scholar at the Department of Mathematics, Covenant University, Ota, Ogun State, Nigeria and he is currently a post-doctoral researcher at the School of Computing, University of Eastern Finland. He holds a Ph.D. in Statistics from the Department of Statistics, University of Ilorin, Kwara State, Nigeria. He is a senior research fellow at the Centre for Multidisciplinary Research and Innovation

(CEMRI) and He is a member of the International Biometric Society (IBS), International Statistical Institute (ISI), Nigerian Statistical Association (NSA), Nigerian Mathematical Society (NMS). He has several conference and journal papers in reputable international bodies, and he has also served as a guest reviewer for several journals. His research interests are data science, machine learning, data mining, biostatistics, categorical data analysis, modeling, and probability distribution models.