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Application of artificial intelligence to toxicological assessment of plant: a bibliometric analysis and future research plans

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Abstract

Artificial intelligence (AI) has gained attention in health science, with significant applications in the toxicological assessment of plants. However, a bibliometric analysis is essential to chart research trends and propose future advancements. This study explores key publications on AI's role in plant toxicity assessment, identifying unresolved issues in pharmacological research. Articles from January 2008 to December 2023 were retrieved from the SCOPUS database, revealing a steady rise in publications, with a sharp increase from 2019 to 2023. A total of 75 research articles were analysed. The articles were categorised into four main clusters: AI applications, drug development, toxicity prediction models, and adverse drug event evaluations. 'AI' was the most frequently mentioned keyword, followed by 'drug toxicity.' Among 64 articles, the USA contributed 29, China 11, India 8, and the UK 4, with the UK having high citation rates. The findings highlight a growing trend toward AI-driven toxicity prediction in drug discovery. However, few studies provide definitive conclusions on AI's potential in this field. The COVID-19 pandemic has heightened interest among researchers and policymakers. This study urges increased government and agency funding for AI-driven toxicity research. Advancing this field will enhance drug safety, reduce harmful testing, and promote sustainable plant use, aligning with SDGs 3, 12, and 15.

1. Introduction

Due to the possible challenges of human biases in toxicological assessment in the plant, there is a dire need in recent times for artificial intelligence to predict potential toxicity and to ascertain off-target outcomes in the pharmacological research workflow. However, there are issues with the threshold of Toxicological Concern (TTC) established to verify the level of chemical exposure between standard chemical toxicity data and below thresholds, which can cause risks to human health (Serafimova *et al.*, 2021; Bury *et al.*, 2021). Further, the purpose of developing the threshold of toxicological concern (TTC) to assess the risk of low-level substances in the diet qualitatively has been attracting the attention of pharmacologists in recent times, triggering the need for artificial intelligence techniques to ascertain the presence of risk substance and the need for comprehensive risk assessment. Therefore, rapid and precise toxicological evaluation of the pharmaceutical products and substances plants is needed to improve medicine production and protect human health (Batke *et al.*, 2021; More, 2019).

Artificial intelligent (AI) is the capacity of the computer to perform human tasks. The foundation of AI applies to the recognition of images in substance. It has developed today into identifying and recognising medical substances in plants and animals to aid the process of complex decision-making, especially in the toxicological assessment of plants for pharmaceutical products (Paul, 2021 & Xu, 2021). Considering the advanced research application of AI in medical sciences, big data in machine learning applications have significantly extended to pharmacological research, such as toxicological assessment of plants for drug manufacturing. Recent evidence has suggested that AI capacity can produce specific and accurate diagnoses of genotoxic impurities in extractables (Bhattamisra, 2023).

Global health issues and the post-COVID-19 era have triggered efforts towards the application of AI in toxicological assessment to derive a 'toxic load' value and relationship that will be representative of all sets of exposure conditions predicted to produce a chosen Specified Level of Toxicity (SLOT) (Busari & Salako, 2024; Sánchez-bayo, 2020). This 'toxic load' can then be used to calculate the risk from the Major Hazard. In recent times, collaborative scientific efforts have developed AI advances to standardise the research process through consolidated standards of reporting trials (CONSORT) and standards for reporting diagnostic accuracy studies (STARD) guidelines. These processes are developed to provide practical guides for applying AI in medical research. There are ongoing studies in using AI for pharmacological development such that the process is completed unsupervised, like the system that works like a 'black box'. Although there are studies about the application of AI to toxicological assessment in plants, little is known about datasets because most AI algorithms work accurately with big datasets to learn from crosscutting information and realities. On the other hand, the available dataset suggests a complication of data labelling and the complexity of the specialised input (Louzao, 2022).

This study, therefore, aimed to conduct a bibliometric analysis and descriptive narrative about existing published qualitative and quantitative work on the application of AI in the toxicological assessment of plants for manufacturing drugs. Amid the scientific survival of the post-COVID-19 pandemic, accurate and sustainable AI toxicological assessment of plants is required for pharmacological research. However, data about the application of AI, like the 'black box' to ascertain plant toxicity, is unresearched; hence, advances in AI and its direction in toxicological assessment for the next decade have not yet been clarified. Thus, we conducted a bibliometric analysis to comprehensively review the AI field in pharmacological research and identify the currently solved and unsolved issues. Furthermore, the study aimed to reveal a research plan and direction for applying AI to the toxicological assessment of plants.

A bibliometric analysis on the Application of AI to Toxicological Assessment of Plants aligns with Sustainable Development Goals (SDGs). It supports SDG 3 (Good Health and Well-being) by advancing safer drug discovery and reducing toxicological risks, SDG 12 (Responsible Consumption and Production) through minimising harmful testing methods, and SDG 15 (Life on Land) by promoting sustainable plant use while protecting biodiversity as posited in the study of Aldousari & Kithinji (2024).

The remaining parts of this paper entail four sections. The first section briefly reviews artificial intelligence and its application to plant toxicological bench research. The second section explicates the methods of data sources and search strategy, while section three describes the search results and key findings. The fourth section presents the conclusion and recommendations for further studies.

2. Artificial intelligent

AI relates to the emulation of human intelligent processes of machines, particularly computer systems. Included in these processes are learning (the gathering of data and rules for utilising that data), reasoning (applying rules for reaching close or exact conclusions), and self-revision (Mohammed & Alkatheiri, 2022).

AI includes many subsets, like machine learning, natural language processing, eyesight, robots, and clever systems. Machine learning, a part of AI, targets forming algorithms that allow computers to learn and make guesses determinations grounded on data (Tripathi, 2023).
AI has applications in nearly all industries, including health care, finance, transportation, and entertainment, along with others. It revolutionises our lifestyles and working systems, improving efficiency, accuracy, and decision-making processes. Nevertheless, AI raises ethical and societal concerns, like job displacement due to automation, algorithm biases, privacy issues, and the potential for misuse in surveillance or warfare. Whilst AI is continuing to advance, it is crucial to address these challenges whilst harnessing its potential for the benefit of humanity (Bajwa *et al.*, 2021).

AI has a variety of applications in medical lab research, offering ground-breaking ways to analyse complicated data, find patterns, and speed up scientific findings. Here are some essential ways AI is utilised in medical bench research:

1) Drug Discovery and Development: AI algorithms can analyse vast datasets to identify potential drug candidates more efficiently than traditional methods. Machine learning models can predict the effectiveness and safety of new compounds, speeding up the drug discovery process and reducing costs (Paul *et al.*, 2021).

2) Genomic Analysis: AI techniques like deep learning analyse genomic data and identify disease-associated patterns. This can lead to discovering genetic markers for disease risk, personalised treatment options, and insights into disease mechanisms (Wardah *et al.*, 2022).

3) Image Analysis: AI-powered algorithms can analyse medical images, such as MRI scans, X-rays, and histopathology slides, to assist in disease diagnosis and prognosis. Deep learning models can detect abnormalities, classify tumour types, and track disease progression accurately (Pinto-Coelho, 2023).

4) Predictive Modeling: AI models can predict patient outcomes, treatment responses, and disease progression based on various clinical and biological factors. These predictive models help researchers understand disease mechanisms, optimise treatment strategies, and improve patient care (Feuerriegel *et al.*, 2024).

5) Drug Repurposing: AI algorithms can identify existing drugs with potential therapeutic effects for new indications by analysing drug databases, molecular structures, and biological pathways. This approach accelerates drug development timelines and reduces costs by repurposing approved drugs for new uses (Prasad & Kumar, 2021).

6) Biomedical Text Mining: AI-powered natural language processing (NLP) techniques extract valuable insights from biomedical literature, including research articles, clinical trials, and electronic health records. This enables researchers to stay updated on the latest findings, discover novel associations, and generate hypotheses for further investigation (Prasad & Kumar, 2021).

7) Personalised Medicine: AI facilitates the development of personalised treatment strategies based on individual patient characteristics, including genetic makeup, medical history, and lifestyle factors. By integrating diverse data sources and employing machine learning algorithms, researchers can tailor interventions to each patient's unique needs, improving treatment outcomes and reducing adverse effects (Johnson *et al.*, 2020).

8) Drug Side Effect Prediction: AI models analyse drug-target interactions, biological pathways, and patient data to predict potential side effects and adverse drug reactions. Early identification of safety concerns enables researchers to prioritise safer drug candidates and mitigate risks during clinical development (Johnson *et al.*, 2020).

AI tools empower medical bench researchers to enhance their processes, delve into intricate biological mechanisms, and expedite scientific breakthroughs. This aims to enhance diagnostics, treatments, and, ultimately, patient well-being.

2.1 Toxicological assessment of plant and artificial intelligent

Toxicological assessment of plants involves evaluating plant-derived compounds or products' potential toxicity or safety for human and environmental health (Sahil *et al.*, 2021).

AI can contribute to the process of toxicological assessment of plants in several ways, as follows:

1) Data Analysis and Modeling: AI algorithms analyse enormous data sets of plant compounds, including chemical structures, biological activities, and toxicity profiles. Machine learning models identify structure-activity relationships (SARs) and predict the toxicity of new compounds based on similarities to known toxicants or safe compounds (Zhu, 2020).

2) Risk Assessment: AI tools assess the risk of exposure to plant-derived toxins by integrating data on chemical composition, exposure pathways, and toxicological effects. Predictive modelling by estimating the likelihood and severity of adverse health outcomes associated with plant consumption or environmental exposure (Zhu, 2020).

3) Dose-Response Modeling: Unveiling the enigmatic dance of dose-response dynamics lies in AI, where techniques like Quantitative Structure-Activity Relationship (QSAR) modelling emerge as torchbearers. These digital magicians not only forecast the intricate interplay between plant toxins and their doses but also weave a tapestry of safe exposure levels for the diverse inhabitants of our ecosystem. Through their cryptic algorithms, they unearth the elusive toxic thresholds, guiding the hand of regulatory guardians in shaping the safety contours of plant-derived marvels (De Prestis *et al.*, 2024).

4) Biological Assays: Embark on a whirlwind journey through the labyrinth of biological assays, where AI reigns supreme, orchestrating a symphony of high-throughput screening. Within this kaleidoscope of experimentation, plant extracts and their solitary compounds undergo a metamorphosis of scrutiny, traversing realms cellularly and virtually. Behold as automated sentinels decode the language of toxicity, utilising cell-based sorcery, biochemical alchemy, and the ethereal whispers of in silico divination. Their insatiable hunger for data births a cascade of revelations, singling out potential toxicants amidst the cacophony of biological activities. Each compound, a protagonist in this narrative of discovery, awaits its fate, poised for further exploration in the grand theatre of science (Xuelian *et al.*, 2023).

5) Adverse Outcome Pathway (AOP) Analysis: Delve into the labyrinthine depths of Adverse Outcome Pathway (AOP) networks, where AI algorithms wield their cognitive prowess to unravel the cryptic molecular mechanisms underlying the enigmatic dance of plant toxin-induced toxicity. With a masterful stroke, they illuminate the clandestine pathways, unveiling the elusive key events that orchestrate this intricate symphony of harm. This arcane knowledge serves as the cornerstone for crafting targeted testing strategies and forging the frontiers of mechanistically-based risk assessment approaches, where the boundaries of understanding blur and the mysteries of toxicity yield to the relentless march of science (Villeneuve *et al.*, 2024).

6) Ecotoxicological Assessment: Peer through the veils of uncertainty into ecotoxicological assessment, where AI models stand as sentinels at the crossroads of environmental fate and ecological consequence. Within this labyrinth of prediction, they navigate the turbulent currents of aquatic and terrestrial ecosystems, their algorithms weaving a tapestry of potentiality and peril. Through the fusion of chemical fate modelling, ecological exposure assessments, and the elusive whispers of toxicity data, researchers embark on a voyage of discovery, charting the environmental risks that shadow the footsteps of plant products in the realms of agriculture and the untamed wilderness (Ceschin *et al.*, 2021).

7) Data Integration and Knowledge Discovery: AI-powered data integration platforms consolidate diverse sources of information on plant toxicity, including literature databases, chemical databases, and omics datasets. By analysing these integrated datasets, researchers can discover novel toxicants, identify biomarkers of exposure or effect, and uncover associations between plant exposure and human health outcomes (Zhu, 2020).

8) Toxico-genomics and Omics Analysis: Enter the realm of toxicogenomics and omics analysis, where AI techniques emerge as sorcerers of interpretation, wielding the arcane arts of machine learning and network analysis to decode the cryptic language of biological data. Within this tapestry of omics (genomics, transcriptomics, metabolomics), they unravel the intricate tapestry of plant toxicity, peering into the molecular abyss to discern the hidden mechanisms that govern harm. Like celestial cartographers mapping the heavenly spheres, they chart the constellations of biomarkers, illuminating pathways of exposure and susceptibility with an otherworldly precision. Like fragments of a cosmic puzzle, these revelations enrich the tapestry of understanding around plant-chemical interactions, beckoning toward the horizon of personalised risk assessment, where every individual is a universe unto themselves (Xuelian *et al.*, 2023).

In recent years, several notable advances in the toxicological assessment of plants have been driven by technological advancements, methodologies, and interdisciplinary collaboration. Here are some key advances:

1) High-Throughput Screening (HTS) Assays: Behold the marvel of High-Throughput Screening (HTS) assays, where the symphony of automation orchestrates a ballet of rapid testing for toxicity within the bosom of plant extracts and compounds. Through the convergence of cell-based, biochemical, and in silico methods, these assays transcend the boundaries of conventional inquiry, propelling researchers into a realm where efficiency dances hand in hand with

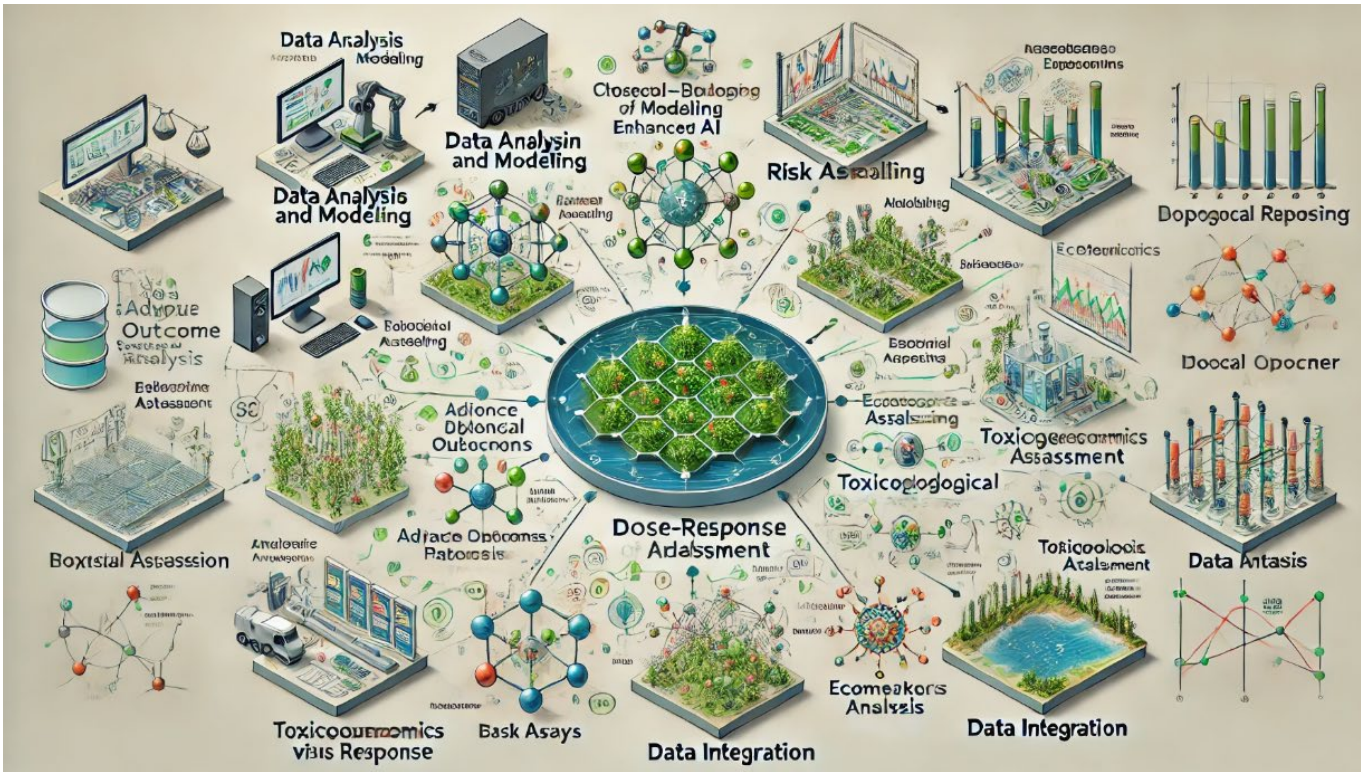

Figure 1: A schematic diagram of the processes involved in the toxicological assessment of plants using AI.

scale. Within the crucible of experimentation, vast armies of samples march in procession, procession, each bearing the potential for revelation or peril. Through the lens of HTS assays, the veil is lifted, hastening the identification of lurking toxicants and unleashing the relentless scrutiny of chemical libraries as the relentless march toward enlightenment gathers pace (Kleinstreuer *et al.*, 2021).

2) Omics Technologies: Peer into the kaleidoscope of Omics Technologies, where genomics, transcriptomics, proteomics, and metabolomics converge to unveil the cryptic tapestry of plant toxicity. Here, within the labyrinth of molecular inquiry, researchers traverse the vast expanse of data, seeking enlightenment amidst the swirling patterns of biological complexity. Through the fusion of Omics data integration and analysis, they unearth the elusive biomarkers of exposure, unfurl the tendrils of toxicity pathways, and sculpt a mosaic of predictive accuracy that transcends the boundaries of conventional understanding (Zong & Guan, 2024).

3) Computational Toxicology: Embark on a voyage through the digital cosmos of Computational Toxicology, where quantitative structure-activity relationship (QSAR) modelling, molecular docking, and toxicogenomics analysis intertwine in a ballet of predictive prowess. Here, within the crucible of computation, researchers wield the tools of virtual inquiry to navigate the labyrinthine pathways of toxicity, charting a course through vast chemical libraries with the precision of cosmic cartographers. Through the alchemy of computational wizardry, they harness the power of data integration to illuminate the shadows of uncertainty, casting a spotlight on the elusive pathways of toxicity with a clarity that defies convention.

4) Multi-Omics Integration: Enter the realm of Multi-Omics Integration, where genomics, transcriptomics, and metabolomics converge in a symphony of biological complexity. Within the tapestry of molecular inquiry, researchers weave a web of understanding transcending individual disciplines' boundaries. By fusing disparate data streams, they unravel the intricate dance of plant compounds and biological systems, illuminating the hidden pathways of toxicity with a clarity that defies expectation (Kleinstreuer *et al.*, 2021).

5) Systems Toxicology: Behold the majesty of Systems Toxicology, where experimental data and computational modelling intertwine in a dance of biological complexity. Here, within the crucible of inquiry, researchers chart the dynamic interactions between multiple biological components, tracing the subtle threads of toxicity across vast biological scales. Through the lens of systems biology, they construct mechanistic models that illuminate the hidden pathways of toxicity, guiding the hand of regulatory decision-making with a clarity that defies convention (Kleinstreuer *et al.*, 2021).

6) Adverse Outcome Pathway (AOP) Framework: Navigates the labyrinth of the Adverse Outcome Pathway (AOP) framework, where toxicological knowledge finds structure amidst the chaos of biological complexity. Here, within the tapestry of regulatory decision-making, researchers chart events from chemical exposure to adverse outcomes, forging

a path through the murky waters of uncertainty. Through the lens of AOP development and application, they translate mechanistic insights into actionable knowledge, guiding the hand of regulatory guardians with clarity that defies expectations (Zong & Guan, 2024).

7) Machine Learning and AI: Witness the dawn of a new era in toxicological assessment, where machine learning and artificial intelligence emerge as titans of predictive prowess. Here, within the crucible of computational inquiry, researchers harness the power of AI to analyse vast and complex datasets, uncovering hidden patterns and associations with a clarity that defies expectation. Through the lens of AI-driven approaches, they illuminate the shadows of uncertainty, guiding decision-makers' hands with a clarity that transcends the boundaries of conventional understanding (Zong & Guan, 2024).

8) Integration of In Vitro and Silico Methods: Peer into the fusion of In Vitro and In Silico Methods, where the strengths of both approaches converge in a symphony of predictive power. Within the crucible of toxicity testing, researchers navigate the complex landscape of compound bioavailability and metabolism, forging a path through the tangled web of biological complexity. Through the fusion of in vitro experimentation and virtual inquiry, they illuminate the hidden pathways of toxicity with a clarity that defies expectation, guiding the hand of decision-makers with a precision that transcends convention (Kleinstreuer *et al.*, 2021).

These advances have significantly improved our ability to assess the safety and toxicity of plant-derived compounds, providing valuable insights into their potential health effects and informing risk assessment and regulatory decision-making. Ongoing research efforts continue to advance the field, driving innovation and enhancing our understanding of plant toxicology.

3. Methods data sources and search strategy

Two authors of the research team screened articles published from 2008 to 2023 in the SCOPUS core collection database for bibliometric analysis.

The study search employed the strategy of the PICO framework. P— population/problem refers to the preclinical toxicity testing of new compounds on animals for the drug development process. In—intervention, our study comprised various AI methods and machine-learning technologies. C—Comparison indicated the difference between AI assistance and physical administration of a substance to the animal. O—outcome, which outlined the results of the physiological effects of AI on the toxicological assessment of plants.

The search strategy was based on information from previous studies and experts' opinions. We used related and specific keywords related to toxicological assessment ('toxicological assessment / toxicological assessment', 'plant toxicity', 'plant toxicity testing', and 'administration of plant substance in an animal'), AI technologies ('artificial intelligence', 'AI', 'machine learning'), and plant substance in animals ('drug toxicity', 'toxicological assessment') in the SCOPUS publication.

We downloaded publications from the bibliometric analysis and extracted the dataset based on the publication details, such as authors and titles. This study employed standard weight attributes link and the total link strength attribute of the articles. The weight attributes describe the frequency of links between items and the total strength of the links between the items.

3.1 Inclusion and exclusion criteria

The articles for bibliometric analysis were restricted to original English-written articles. The exclusion criteria were (I) non-English written documents and (II) documents classified as nonoriginal articles.

3.2 Statistical analysis

The study used the intrinsic functions of the SCOPUS core collection database by IIUM to describe the basic features of the detected publications. VOS viewer (version 1.6.19; for Microsoft Windows) was used to construct and visualise co-occurrence networks of co-authorship, co-occurrence, citation, and keyword search. The VOS viewer defined keywords that occurred more than five times as high-frequency keywords. VOS viewer clustering algorithms were used to calculate all the algorithms based on previous guidelines (10).

4. Results

4.1 Publications output

A total of 77 eligible publications were selected, of which 406% were original articles, 233% were reviewed, 111% were conference papers, 29% were book chapters, and 14% were other types of articles. It should be noted that almost half of the eligible publication's articles (34.6%) were published between 2021- 2023. Ultimately, 803 English-written research articles were included in the bibliometric analysis (Figure 1).

4.2 Growth trend of publications

A steady growth in the number of publications in this field between 2014 and 2020 was detected, while the search showed a rapid increase in the number of articles in this study area from 2021 to 2022 (Figure). The total number of articles published before 2021 was (228) while 306 were published between 2021 and 2022 alone. This shows that the two-year publication was about 62 more than the range of research in this field between 6 years. The search detected about 74 countries' contributions to the field of artificial intelligence/machine language in toxicological assessment-related research. The United States of America (USA) has the most publications of about (n=249) articles, followed by China (n=127), India (n=93), and the United Kingdom (n=76), respectively. At the same time, other countries, mainly those in Europe and Asia, had the remaining publications. Keyword searches identified by the VOS viewer are based on the citation index service of the SCOPUS core collection database. Finally, 1415 keywords were identified from the included articles, with 169 meeting the thresholds based on 3 occurrences. Among them, 27 keywords were high-frequency and included in the analysis.

Bibliometric analysis of keywords

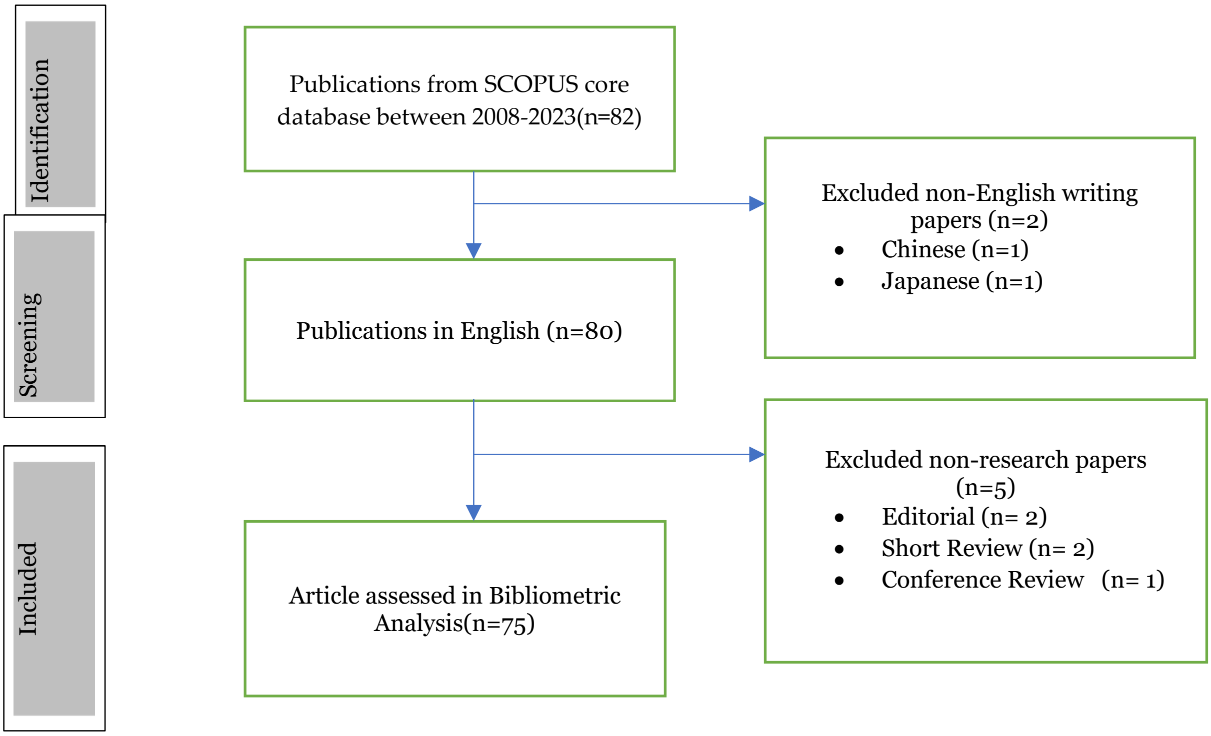

Figure 2: Flow diagram of the article selection process: SCOPUS.

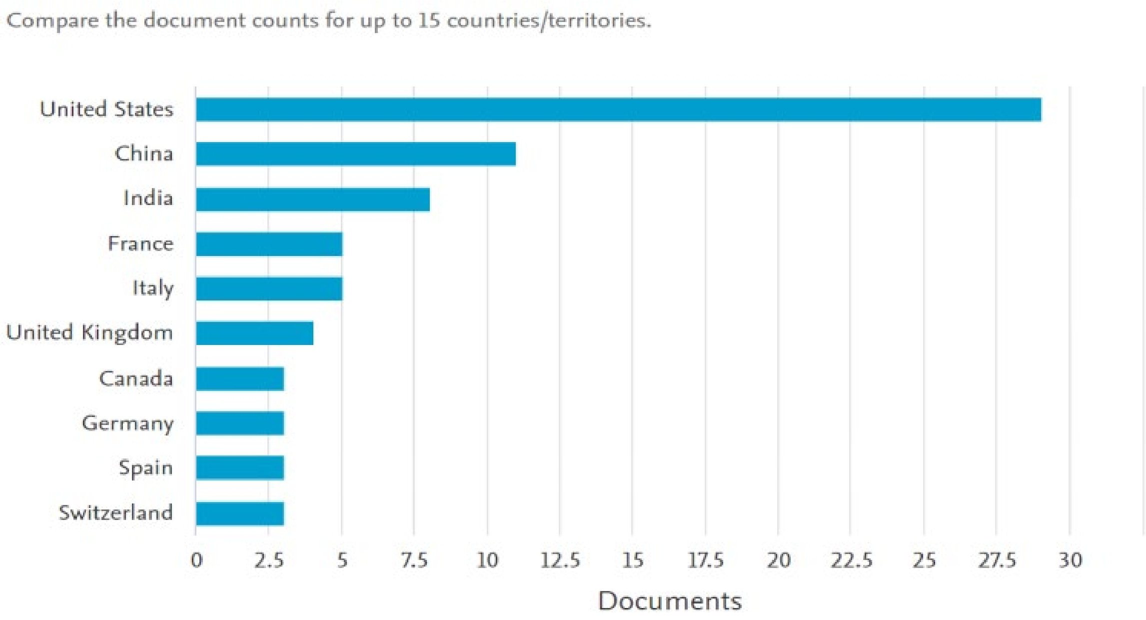

Figure 3A: Comparison of the documents based on countries.

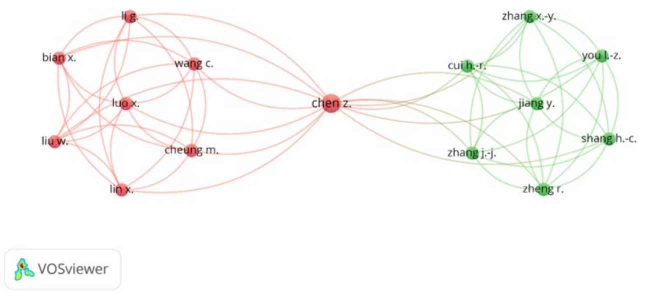

Figure 3B: Co-authorship and complete counting.

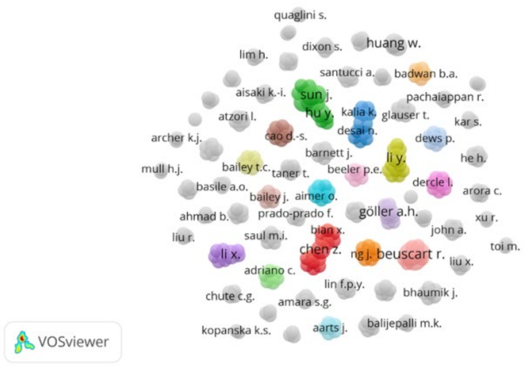

Figure 4A: Co-authorship and complete counting.

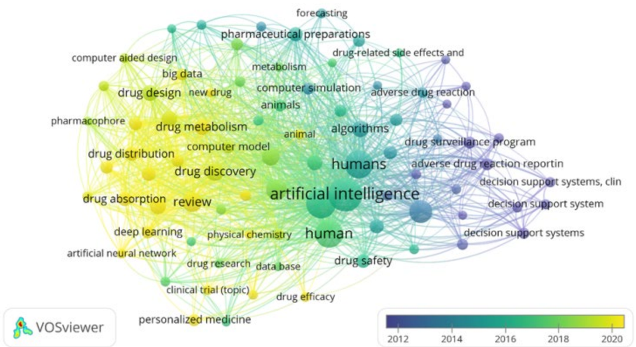

Figure 5: Keywords co-occurrence with full counting method.

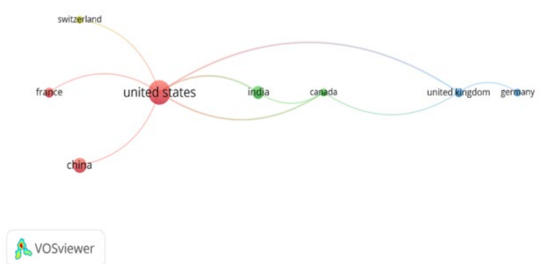

Figure 6: Co-authorship by countries with the whole counting method.

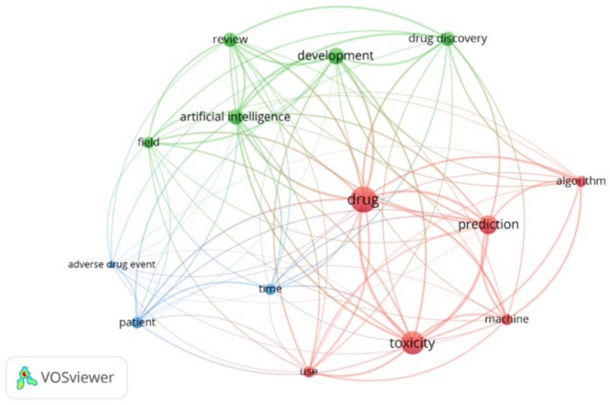

Figure 7: Kinds of research cluster.

5. Discussion of findings

Co-authorship and complete counting found a particular author repeatedly having co-authorship on the subject matter. This means that when examining co-authorship and conducting a comprehensive count of occurrences, it was discovered that a specific author repeatedly collaborated with others on the same topic or subject. This phenomenon is crucial in bibliometric analysis as frequent co-authorship reflects intellectual leadership and collaboration networks. The whole counting method, which equally credits all authors, highlights the recurrent contributions of a specific author quantitatively (Lim & Kumar, 2024).

In co-occurrence with full counting search, the keywords artificial intelligence, human, drug safety, and pharmaceutical preparation are in order of the highest frequency occurrence. This indicates that during a co-occurrence analysis alongside a full counting search, the keywords 'artificial intelligence', 'human', 'drug safety', and 'pharmaceutical preparation' appeared most frequently, with their order based on their frequency of occurrence. Using the complete counting method, co-occurrence analysis effectively identifies dominant research topics by assigning equal weight to each keyword occurrence, reflecting their significance in shaping research trends (Senthil *et al.*, 2024).

According to the search of different research clusters, the order of highest occurrence is 'drug' prediction, toxicity, and artificial intelligence, and drug development is the keyword with the highest clusters. This suggests that in a search focusing on types of research clusters, the keywords with the highest occurrence were 'drug prediction', 'toxicity', and 'artificial intelligence', with a particular emphasis on 'drug development' as the keywords with the highest clusters. According to Chen (2012), these terms strongly emphasise AI-driven predictive models for toxicity and drug discovery, reflecting significant advancements in these areas. Such keyword clustering is instrumental in identifying research priorities and guiding interdisciplinary collaboration in pharmacological development.

These results suggest a strong focus on collaborative authorship within a particular subject area, possibly in academia or scientific research. Additionally, they indicate that specific keywords like 'artificial intelligence', 'drug safety', 'pharmaceutical preparation', 'drug prediction', 'toxicity', and 'drug development' are significant topics of interest within this research context. This information could imply trends in research priorities, potential areas of expertise for the authors involved, or emerging themes in the field. Collaborative keyword search trends indicate a shift toward AI-driven approaches in pharmacology and safety assessment, aligning with broader healthcare goals, while the frequent occurrence of specific keywords signals author specialisation and highlights emerging themes that could shape future developments in the field.

The Vosviewer analysis shows that the term: 'AI' has the highest frequency keyword (73 occurrences, 848 total links strength) while the 'drug toxicity' keyword (56 occurrences, 767 total link strength) was the second most frequent keyword, followed by human, machine learning, and drug discovery. Based on 75 academic articles, the United States of America (USA) had the highest frequency of 29 documents with (675 citations and 9 total link strength), followed by China with 11 with (223 citations and 9 total link strength) and India with 8 (118 citations and 9 total link strength) respectively. The documents from the United Kingdom have only 4 articles, with (253 citations and 4 total link strengths).

6. Conclusion

Recent attention has been drawn to the utilisation of AI in forecasting drug toxicity, particularly heightened during the COVID-19 crisis. Encouraging collaborative financing between governmental bodies and organisations is imperative to delve deeper into AI's advancements in this domain. The burgeoning research underscores its potential in medical sciences and human welfare. The application of AI to the prediction of drug toxicity in drug discovery and development is a research field with great potential. In the post-COVID-19 era, there is a dire need to enhance cooperative policy support between government agencies and funding for AI in drug development. Although growing numbers of studies focus on decision-making using AI applications in drug toxicity and prediction models in drug development, findings suggest that researchers in a particular field are teaming up frequently, indicating a strong collaborative culture. Moreover, specific topics like artificial intelligence and drug safety seem to be hot research areas, likely driving advancements in related fields such as pharmaceutical development.

Therefore, this research contributes by identifying key trends in the application of AI in pharmacology, particularly for drug safety and development. It highlights emerging themes and areas of expertise, revealing shifts toward AI-driven solutions and emphasising collaborative authorship. These insights guide future research priorities and potential innovations in healthcare.

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