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Review

Visual Analytics in Pharmacovigilance: A Scoping Review

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Abstract

Visual analytics combines computational analysis with interactive visual representations and may strengthen pharmacovigilance, but its use in drug safety research has not been systematically characterized. This scoping review mapped the extent, characteristics, and applications of visualization and visual analytics in pharmacovigilance and identified evidence gaps. Following Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidance, we searched PubMed, IEEE Xplore, Web of Science, Scopus, and Google Scholar from inception through April 2026. Two reviewers independently selected studies and extracted data, which were synthesized qualitatively using predefined frameworks covering pharmacovigilance activities, analytical methods, visual representations, and interaction capabilities. Sixty-seven studies met the eligibility criteria: 41 system design studies and 26 non-system studies. Of the designed systems, 29 were classified as visual analytics systems and 12 as interactive visualization systems. Signal management was the most frequently supported activity; plots and charts were the predominant visual representations; and selecting, filtering, and drilling were the most common interactions. Only 16 systems reported formal evaluations. Visual analytics has been applied across diverse pharmacovigilance activities, particularly signal management, but the field remains limited by incomplete end-to-end workflow support, restricted analytical transparency, limited integration of complementary evidence sources, and infrequent formal evaluation of designed systems.

Keywords: visual analytics; pharmacovigilance; scoping review; drug safety monitoring; information visualization

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Academic Editor: Antony Bryant

Received: 6 August 2026
Revised: 3 September 2026
Accepted: 4 September 2026
Published: 8 September 2026

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1. Introduction

Medication-related harm is a major public health issue that causes significant, often preventable, morbidity, mortality, and economic costs [1,2]. As adverse drug events (ADEs) require timely detection and intervention, pharmacovigilance plays a critical role. It provides the essential post-marketing infrastructure to identify and manage rare, delayed, or population-specific safety signals that standard pre-marketing clinical trials are too limited to capture [3–5].

Modern pharmacovigilance relies on a diverse ecosystem of data, drawing from foundational spontaneous reporting systems as well as electronic health records (EHRs) and claims data [6,7]. While utilizing multiple sources improves evidence quality, it introduces substantial analytical challenges. Analysts must navigate fragmented reporting structures and complex, longitudinal patient histories that cannot be easily captured in static tables [8]. Furthermore, safety data is often high-dimensional, noisy, incomplete,

and subject to biases such as underreporting [9,10]. Consequently, the primary challenge is not merely accessing data but also effectively reasoning through complex associations between drugs, events, and patient characteristics [11].

Visual analytics addresses this complexity by combining computational analysis with interactive visual interfaces [12–14]. Rather than presenting static outputs, it allows analysts to dynamically explore temporal patterns, compare subgroups, evaluate missing data, and investigate underlying evidence for candidate safety signals [15,16]. By actively structuring the analysis process, visual analytics empowers domain experts to identify patterns, question assumptions, and refine decisions in real time [17,18].

The literature on visual analytics in pharmacovigilance remains fragmented and is methodologically and conceptually heterogeneous, encompassing diverse users, data environments, pharmacovigilance activities, analytical methods, visual representations, interaction techniques, and evaluation objectives. Although previous reviews have examined adverse event reporting, signal detection methods, and visual analytics in broader healthcare contexts [12,19,20], no comprehensive review has specifically mapped the application of visual analytics within pharmacovigilance. Consequently, it remains unclear which data sources and analytical methods are integrated, which visualization and interaction approaches are most employed, how systems are evaluated, and where important methodological and research gaps persist. Such a review is particularly important because pharmacovigilance involves high-stakes decisions concerning rare and uncertain drug-related harms, creating domain-specific requirements for how analytical evidence is interpreted and communicated. Given the breadth and heterogeneity of this evidence, direct comparison and quantitative synthesis are not appropriate. A scoping review is therefore well suited to systematically map the extent and characteristics of the literature, clarify how visualization and visual analytics have been conceptualized and applied in pharmacovigilance, and identify areas requiring further investigation. Accordingly, this review addressed the following questions:

- What types of evidence have been published on visualization and visual analytics in pharmacovigilance, and what data sources and application contexts characterize this literature?
- Which pharmacovigilance activities and analytical tasks are supported, and what visualization techniques, interaction capabilities, and computational methods have been employed?
- How have pharmacovigilance visualization and visual analytics systems been evaluated?
- What methodological, technological, and evidence gaps remain, and what priorities for future research can be identified?

2. Materials and Methods

We conducted this review in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines. A protocol for this scoping review was not prospectively registered or published. The completed PRISMA-ScR checklist is available in Supplementary File Table S1.

2.1. Eligibility Criteria

Studies were included in the review if they met all the following criteria: (a) research focusing on development of a visual analytics/interactive visualization system for pharmacovigilance/ADEs or non-system research where visualization is used as an explicit analytic or communication method or that provides guidelines, conceptual frameworks, or recommendations for utilization of visual analytics in drug safety; (b) studies published in

peer-reviewed journals or conference proceedings; (c) studies written in English language; and (d) studies published from database inception until 27 April 2026.

Studies were excluded from the review if they met any of the following criteria: (a) studies that provided no figure or form of representation for observing and analyzing the designed visualization; (b) studies not written in English language; and (c) studies not relevant to pharmacovigilance or drug safety monitoring.

Peer-reviewed journal articles and conference proceedings were included because these publication types were expected to provide sufficient methodological and technical detail for charting system characteristics. The review was restricted to English-language publications because resources for translation were unavailable. Moreover, studies that provided no figure or form of representation were excluded because they provided no basis for extracting designed system elements.

2.2. Information Sources and Search Strategy

We conducted a scoping literature review to retain all the studies between database inception and 27 April 2026. We collected all the studies that either designed a visual analytics/interactive visualization system or provided conceptual framework, guideline or recommendations for visualizations in the field of pharmacovigilance. We categorized search keywords into three categories of (a) visual, (b) analytics, (c) and pharmacovigilance, as presented in Table 1.

Table 1. Keywords used in search strategy and their categories.

Category	Keywords
Visual	Visual, Visualization
Analytics	Analytics, Analysis, Data mining, Machine learning
Pharmacovigilance	Pharmacovigilance, Drug Monitoring, Adverse Drug Events, Adverse Drug Reactions, Drug Related Side Effects, Drug Toxicity

We systematically searched PubMed, IEEE Xplore, Web of Science, Scopus, and Google Scholar using the three categories of keywords. The details of search strategies for each database are presented in Table 2.

Table 2. Search query used in each database and number of documents retrieved.

Database	Search Query	Total Retrieved Studies
PubMed	(visualization[Title/Abstract] OR visual[Title/Abstract])AND (analytics[Title/Abstract] OR analysis[Title/Abstract] OR "data mining"[Title/Abstract] OR "machine learning"[Title/Abstract]) AND ("Drug Monitoring"[Title/Abstract] OR "Drug-Related Side Effects and Adverse Reactions"[MeSH] OR "drug safety"[Title/Abstract] OR "drug toxicity"[Title/Abstract] OR "adverse drug reaction*"[Title/Abstract])	461
IEEE Xplore	("All Metadata":"visualization" OR "All Metadata":"visual") AND ("All Metadata":"analytics" OR "All Metadata":"analysis" OR "All Metadata":"data mining" OR "All Metadata":"machine learning") AND ("All Metadata":"drug monitoring" OR "All Metadata":"adverse drug event*" OR "All Metadata":"adverse drug reaction*" OR "All Metadata":"drug related side effect*" OR "All Metadata":"drug toxicity" OR "All Metadata":"drug safety")	38

Table 2. *Cont.*

Database	Search Query	Total Retrieved Studies
Web of Science	TS = ((visualization OR visual) AND (analytics OR analysis OR "data mining" OR "machine learning") AND ("drug monitoring" OR "adverse drug event*" OR "adverse drug reaction*" OR "drug related side effect*" OR "drug toxicity" OR "drug safety"))	439
Google Scholar	(intitle:visualization OR intitle:visual) ("data mining" OR "machine learning" OR analytics OR analysis) ("drug monitoring" OR "adverse drug reaction" OR "drug safety" OR "drug toxicity")	866
Scopus	(TITLE-ABS-KEY (visualization OR "visual analytics") AND TITLE-ABS-KEY (analytics OR "data mining" OR "machine learning") AND TITLE-ABS-KEY ("drug monitoring" OR "adverse drug event*" OR "adverse drug reaction*" OR "drug related side effect*" OR "drug toxicity" OR "drug safety"))	188

* Indicates a wildcard used to retrieve variations of a term with different word endings.

2.3. Study Selection and Data Collection Process

We conducted the study selection in two distinct stages. First, two reviewers independently screened titles and abstracts to evaluate relevance. They advanced potentially eligible citations to the next round and excluded the rest, with a third reviewer resolving any disagreements. Next, two independent reviewers assessed the full texts of the remaining articles. We documented specific reasons for any exclusions at this stage. If the reviewers disagreed on a study's inclusion, they reached a consensus through discussion or by deferring to a senior reviewer. Subsequently, two reviewers independently extracted the data, resolving any disagreements through discussion or by consulting a third reviewer. The charting tables used for extracting information are available in Supplementary File Tables S2 and S3.

2.4. Data Items

We extracted the following data points from the included system design studies:

- Study Characteristics: We recorded the publication year, the specific data sources used, and the authors' rationale for developing the system.
- System Characteristics: We documented a brief description of the system, the intended stakeholders, and the specific pharmacovigilance activities it supports. We also detailed the visualization and interaction techniques employed and identified the analytical engine used in any visual analytics systems.
- System Evaluation: We assessed whether the authors conducted a formal user study to measure usability or user experience, and we extracted the corresponding results.

Furthermore, the following data points were extracted from the non-system design studies:

- Study Characteristics: We recorded the publication year and classified each study according to its primary contribution type, including bibliometric and visual analyses, guidance papers, novel visualization designs, and scientific reporting studies. We also extracted the primary objective of each study to capture whether the paper aimed to map research trends, provide methodological recommendations, introduce a specific visualization approach, or report pharmacovigilance findings using visual or analytical methods.
- Methodological Characteristics: We extracted each study's analytic methods and data sources.

- Pharmacovigilance Focus: We extracted the pharmacovigilance activity or purpose addressed by each study and recorded how it contributed to drug safety analysis, communication, or decision-making.
- Visualization Characteristics: We documented the visualization techniques used or recommended in each study

2.5. Data Synthesis

The main synthesis approach was qualitative due to the nature of the studies in this review, and no meta-analysis was performed. However, we used a framework in our analysis of the studies that are described below.

2.5.1. Pharmacovigilance Activities Framework

For pharmacovigilance activities, we used Beninger's study [21], which defines pharmacovigilance (PV) as a broad set of scientific and operational activities concerned with the detection, assessment, understanding, communication, prevention, and management of drug-related harms.

Case management: The standardized collection, coding, evaluation, and reporting of individual adverse event information.

Signal management: Querying safety data, identifying potential drug–event relationships, assessing whether a safety concern requires further investigation, and determining whether regulatory or clinical communication is needed.

Benefit–risk management: Extends these activities by placing identified or potential risks in relation to the therapeutic benefits of a product and by supporting risk minimization strategies.

2.5.2. Visualization Framework

Visualizations will be analyzed using Parsons and Sedig's study [22], which categorizes visualization based on how different visual forms support perception, reasoning, sensemaking, decision-making, and knowledge discovery. Based on their study, we used the following definitions:

- Visual encodings and marks: Basic building blocks of visualization, such as lines, dots, shapes, color, size, and orientation.
- Glyphs and multidimensional icons: Integrate several visual encodings into a single object, which allows multiple attributes to be perceived together; examples include Chernoff faces, Clockeye/ClockMap glyphs, star glyphs, timewheels, kite diagrams, and whisker glyphs.
- Plots and charts: Organize information within coordinate systems, which are useful for detecting distributions, comparisons, trends, anomalies, outliers, and possible relationships; examples include scatterplots, bar and column charts, line charts, area charts, radar charts, contour plots, surface graphs, and parallel coordinates.
- Maps: Spatially arrange information so that geometric position, distance, density, or region supports reasoning about spatial or spatialized patterns; examples include thematic maps, choropleth maps, topographic maps, weather maps, cartograms, heat maps, and self-organizing maps.
- Graphs, trees, and networks: Use links, arrows, nodes, and other connectors to make relationships explicit, which supports reasoning about structure, movement, dependency, hierarchy, or association; examples include node-link diagrams, radial networks, flow diagrams, decision diagrams, concept maps, cone trees, and hyperbolic trees.
- Enclosure diagrams: Use bounded regions or tabular structures to communicate grouping, membership, inclusion, exclusion, and precise lookup; examples include

Venn diagrams, Euler diagrams, Voronoi diagrams, adjacency matrices, contingency tables, treemaps, sunbursts, and DocuBursts.

2.5.3. Interaction Framework

For the analysis of available interactions, we used Sedig and Parsons' EDIFICE-AP framework [23], which conceptualizes interaction in visualization-based tools as a set of epistemic action patterns that support complex cognitive activities such as sense-making, analytical reasoning, decision-making, problem solving, learning, and knowledge discovery. Rather than classifying interaction only by interface-level techniques, such as clicking, dragging, hovering, or using menus, this framework focuses on the underlying cognitive purpose of the interaction: what the user is able to do with the visual representation in order to inspect, transform, organize, reveal, compare, or refine information.

3. Results

3.1. Study Selection

Our initial search resulted in 1992 potentially relevant studies comprising 461 studies from PubMed, 38 studies from IEEE Xplore, 439 studies from Web of Science, 866 studies from Google Scholar, and 188 studies from Scopus. After removing 1211 duplicate studies, we screened 781 unique studies. Based on title and abstract screening, 652 records were excluded, as they did not meet our eligibility criteria. The remaining 129 studies underwent full-text review, which resulted in the exclusion of 62 additional studies. Common reasons for exclusion at the full-text stage included the study not presenting any figure or form of representation for observing and analyzing the designed visualization (n = 1), not having access to the study (n = 4), studies not written in the English language (n = 12), and studies not relevant to pharmacovigilance or drug safety monitoring (n = 45). Among the 12 studies excluded due to the English-language restriction, two appeared potentially relevant to the use of visualization in pharmacovigilance based on the available information.

Ultimately, 67 studies met all inclusion criteria and were included in our scoping review, from which 26 were non-system studies and 41 studies designed either an interactive visualization or a visual analytics system. Of the 41 system design studies, 29 were classified as visual analytics systems because they combined interactive visualizations with an embedded analytical engine. The remaining 12 were classified as interactive visualization systems because they supported interactive exploration but did not include substantial computational analysis beyond data retrieval, aggregation, or visual encoding. The study selection process is detailed in the PRISMA flow diagram (Figure 1).

3.2. Non-System Studies

Of the final pool of included studies, 26 were classified as non-system design studies. Figure 2 provides an overview of these studies. Below, we have provided a summary of these studies based on their categories:

3.2.1. Bibliometric and Visual Analysis Studies

Eleven studies used bibliometric, scientometric, and visual knowledge mapping approaches to characterize the development of pharmacovigilance, medication safety, and ADE research. These studies primarily employed quantitative mapping techniques to analyze publication patterns, collaboration networks, and thematic trends, ultimately characterizing the structural evolution of pharmacovigilance and ADE research.

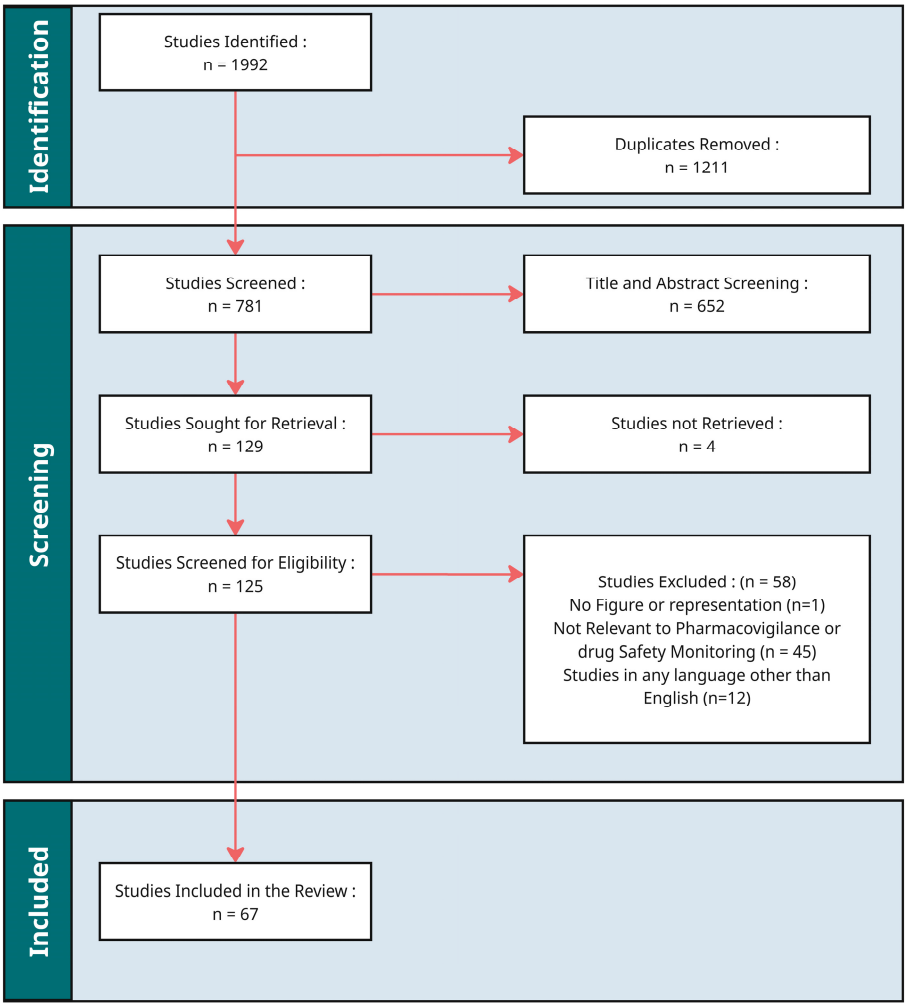

Figure 1. PRISMA flow diagram for study selection process.

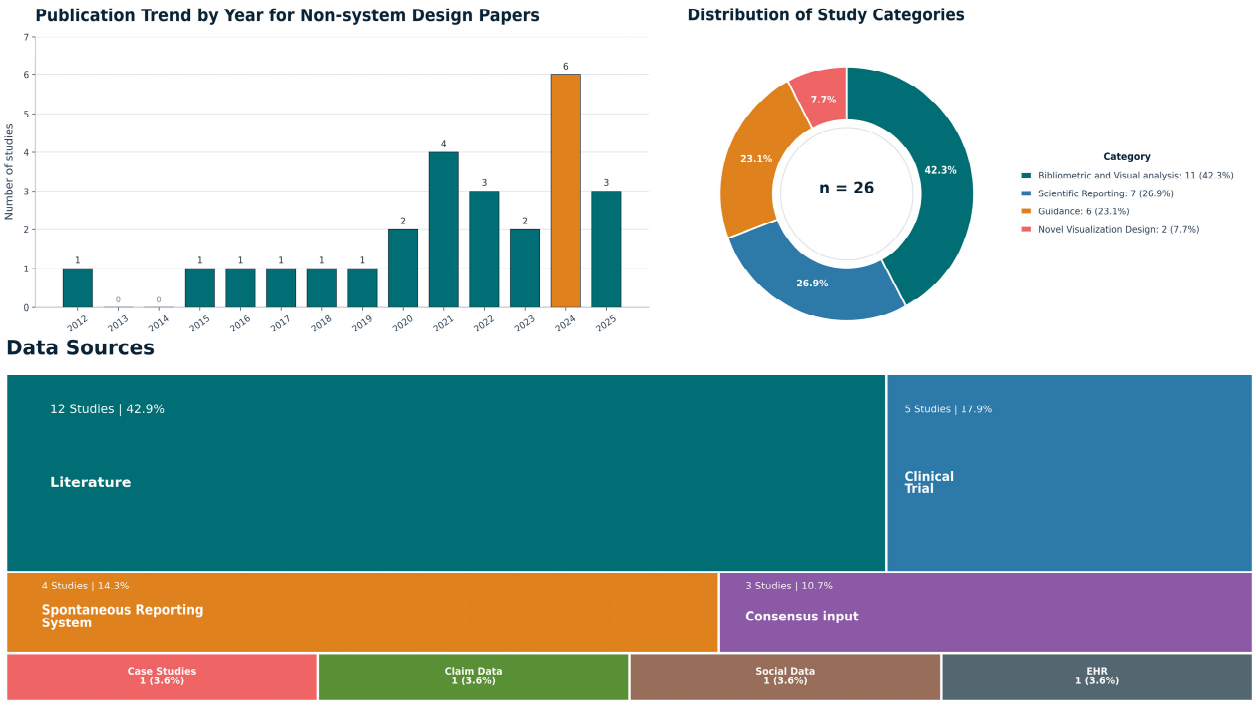

Figure 2. Overview of the non-system studies.

Several studies examined broad trends in pharmacovigilance and ADE research. Wang et al. [24] analyzed 2128 articles published between 1974 and 2021 to examine the overall development of pharmacovigilance research. Using VOSviewer (version 1.6.17), CiteSpace (version 5.8.R1), CitNetExplorer (version 1.0.0), and bibliometric.com [25], the authors visualized collaboration networks, citation relationships, and research hotspots. Their findings showed increasing scholarly attention to pharmacovigilance over time, with ADEs, pharmacoepidemiology, drug safety, and signal detection identified as central themes. Emerging areas included VigiBase, FDA Adverse Event Reporting System (FAERS), disproportionality analysis, social media, patient safety, and preventability. Similarly, Litvinova et al. [26] investigated the application of digital technologies in ADE management. Based on 1241 Web of Science publications from 1991 to 2023, the study used VOSviewer (version 1.6.18) to identify thematic clusters related to the prevention, detection, and management of ADEs.

Other studies focused on specific therapeutic areas, drug classes, or adverse event domains. Gong et al. [27] examined research on immune-related adverse reactions in lung cancer immunotherapy using Web of Science publications from 1991 to 2023. Through VOSviewer (version 1.6.19 basic) and CiteSpace (version 6.2.R5 advanced), they analyzed publication trends, geographic and institutional contributions, journal influence, keyword co-occurrence, citation bursts, and temporal shifts in research topics. Relatedly, Song et al. [28] analyzed 1477 publications on adverse events associated with PD-1/PD-L1 inhibitors from 2014 to 2024 using VOSviewer (version 1.6.18), CiteSpace (version 5.7.R5), Bibliometrix, and Biblioshiny (version 4.1.2) [29]. Zhao et al. [30] focused on the association between immune-related adverse events and prognosis in immune checkpoint inhibitor therapy, analyzing 724 Web of Science records from 2007 to 2023 with CiteSpace (version 6.1.R6) and VOSviewer (version 1.6.18) to examine countries, institutions, authors, journals, cited references, keyword co-occurrence, bursts, and thematic clusters.

A number of studies applied similar bibliometric and visualization methods to medication safety issues in specific populations or clinical contexts. Wei et al. [31] analyzed 1201 Web of Science records up to 2023 on drug-related side effects and adverse reactions in migraine treatment. Using VOSviewer (version 1.6.19), Scimago Graphica (version 1.0.35), CiteSpace (version 6.2.R4), and bibliometrix (version 4.3.1) [32,33], the authors mapped publication trends, influential journals, authors, institutions, countries, keywords, and cited references. Wu et al. [34] examined drug-induced cardiotoxicity in children using 298 Web of Science articles retrieved up to 2022 and applied CiteSpace (version 5.8.R3) and VOSviewer (version 1.6.18) to visualize the structure of the field. Wang et al. [35] similarly investigated anthracycline-induced cardiotoxicity from 2002 to 2021, analyzing 3504 Web of Science publications with bibliometrix (R version 4.1.2), VOSviewer (version 1.6.17), and CiteSpace (version 5.8.R3). Xie et al. [36] focused on medication safety research among older adults, using 1638 Web of Science publications from 2000 to 2021 to map collaboration networks, citation structures, and keyword bursts through CiteSpace and VOSviewer. Luo et al. [37] conducted a knowledge mapping analysis of global drug hypersensitivity research from 2013 to 2023, using 4299 Web of Science publications and CiteSpace to visualize networks of countries, institutions, authors, journals, references, and keywords.

More recent work has also connected bibliometric mapping with computational methods such as artificial intelligence (AI), machine learning, and natural language processing (NLP). Abisado et al. [38] conducted an NLP-supported scientometric analysis of adverse drug effect reporting and AI-driven pharmacovigilance. Using 74 Scopus-indexed publications from 2014 to 2025, the authors applied VOSviewer and Biblioshiny to examine publication trends, influential sources, productive authors, country contributions, key-

word co-occurrence, and thematic clusters. Their analysis emphasized the increasing use of NLP and machine learning for extracting ADE signals from informal data sources, while also identifying continuing challenges related to data reliability, privacy, ethics, and algorithmic bias.

Overall, these studies suggest that visualization has been widely used in pharmacov igilance-related research as a means of mapping scholarly activity, identifying influential contributors, and detecting thematic shifts over time. However, their primary contribution lies in describing the structure and evolution of research fields rather than supporting direct pharmacovigilance activities. Figure 3 shows the distribution of visualization tools used in these papers.

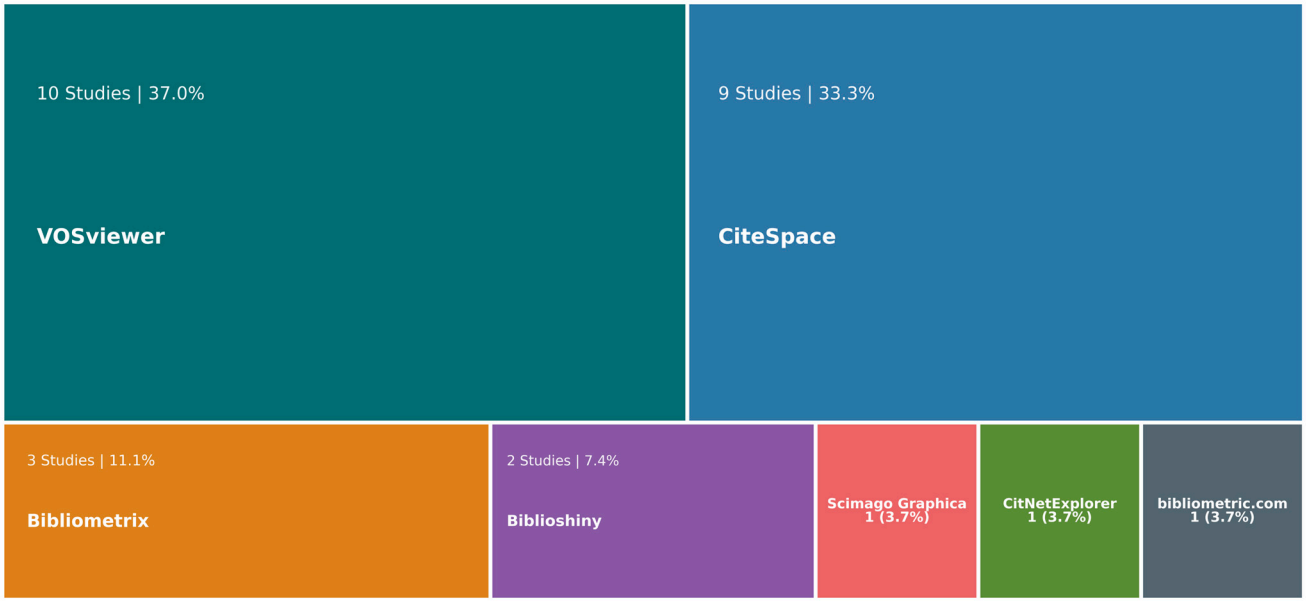

Figure 3. Distribution of visualization tools used in bibliometric analysis studies.

3.2.2. Novel Visualization Design Studies

Two studies proposed novel visualization techniques for representing complex safety information in clinical trials, demonstrating how visualizations can be utilized to encode multiple dimensions of safety data in pharmacovigilance.

Karpefors and Weatherall [39] introduced the tendril plot (Figure 4) as a novel method for summarizing adverse events across an entire clinical trial. Each adverse event term is represented as a branch that grows over time, with events in one treatment arm bending the branch in one direction and events in the comparator arm bending it in the opposite direction. This design allows the viewer to identify not only whether adverse events are imbalanced between treatment groups, but also when those imbalances emerge and whether they persist or resolve. The method was also presented as suitable for interactive exploration through filtering, zooming, hovering, and linking to detailed views. However, the authors noted limitations, including difficulty extending the method beyond pairwise treatment comparisons and the need for further statistical and clinical review after potential signals are identified.

Tesfaldet et al. [40] proposed a composite plot (Figure 5) for visualizing changes in trials involving subjects with abnormal baseline liver tests. The plot extends traditional evaluation of drug-induced serious hepatotoxicity (eDISH) displays by combining population-based upper-limit-of-normal thresholds with subject-specific baseline changes. This allows reviewers to assess whether on-treatment liver test abnormalities represent possible drug-induced liver injury, pre-existing abnormality, or potential improvement

from baseline. The visualization supports the interpretation of subject migration across eDISH quadrants and helps identify outliers requiring case-level assessment.

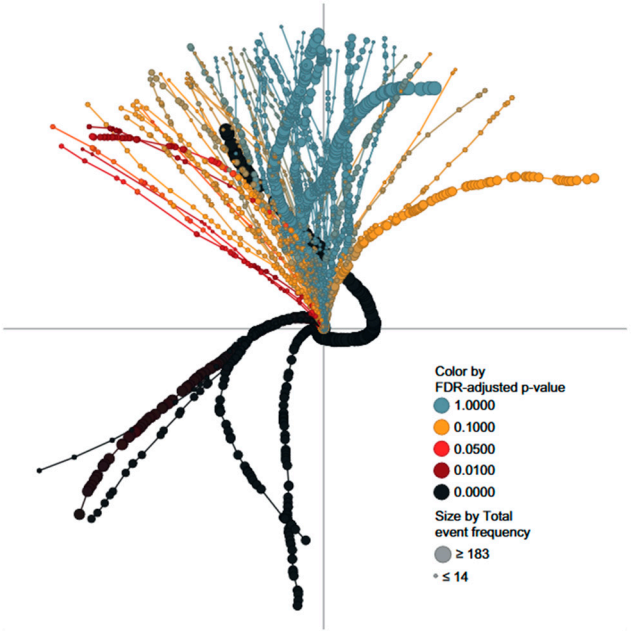

Figure 4. A tendril plot of all adverse events in a clinical trial. Each Medical Dictionary for Regulatory Activities (MedDRA) PT is represented by a line (tendril), and each point is an event. Source: Image by Karpefors and Weatherall [39].

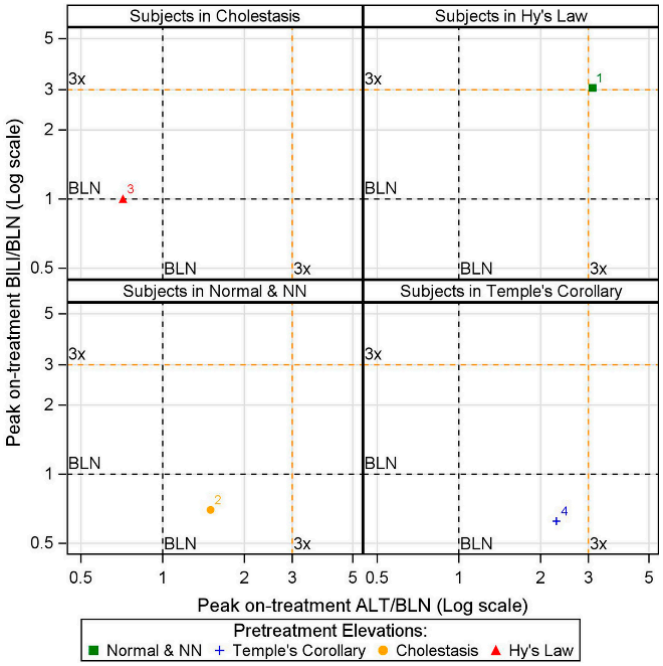

Figure 5. The composite Evaluation of drug-induced serious hepatotoxicity (eDISH) plot. Source: Image by Tesfaldet et al. [40].

3.2.3. Guidance Studies

Six studies provided guidance, recommendations, or methodological direction on the use of visualization and visual analytics for communicating, evaluating, and interpreting safety-related information. These papers focused on how visual representations can support pharmacovigilance-related reasoning in clinical trials, benefit–risk assessment, safety review, and model-based decision-making.

Several papers focused specifically on the communication of harms and adverse events in randomized controlled trials. Cornelius et al. [41] argued that conventional frequency tables are often insufficient for evaluating large numbers of adverse events because they require readers to manually compare event rates across arms and may obscure potentially meaningful safety patterns. Using case studies from placebo-controlled trials, the authors demonstrated the value of volcano plots and dot plots for summarizing multiple adverse events. The volcano plot was presented as a useful signal-oriented display because asymmetry can draw attention to events that differ between treatment arms, while the dot plot was shown to provide a more comprehensive representation by combining absolute risks, relative comparisons, confidence intervals, and event counts. Importantly, the authors also cautioned that visualizations can overemphasize treatment effects when event numbers are small and therefore recommended that graphical displays be interpreted alongside crude numerical data.

Phillips et al. [14] extended this line of work through a consensus study that developed recommendations for visually presenting harm outcomes in randomized controlled trial publications. The study considered 28 candidate visualizations and endorsed 10 for use in main trial reports, with the choice of visualization guided by outcome type, analytic scenario, and purpose of communication. For binary harm outcomes, the authors recommended dot plots for summarizing multiple outcomes and stacked bar charts when severity information is important. For recurrent or count outcomes, bar charts and mean cumulative function plots were recommended, depending on whether temporal information was required. For continuous harm outcomes, the recommendations included scatterplot matrices, line graphs, violin plots, and kernel density plots, while time-to-event harms could be communicated using Kaplan–Meier plots and survival ratio plots. A key contribution of this work was the decision tree (Figure 6), which operationalized visualization selection by linking data characteristics and analytic goals to appropriate plots. This provides a practical framework for trialists and statisticians to move beyond default tabular reporting and toward more intentional visual communication of harm profiles.

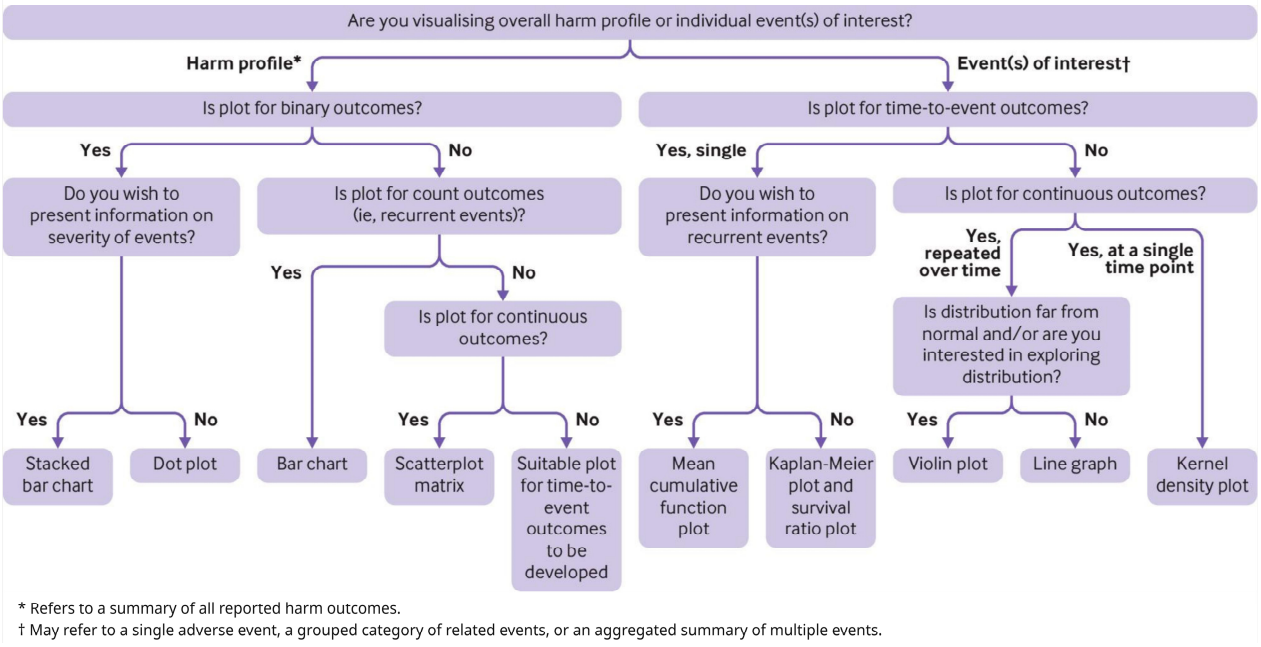

Figure 6. Decision tree for selecting visualizations based on data characteristics and analytical goals. Source: Image by Phillips et al. [14].

Qureshi et al. [42] compared the value of six visualization approaches for communicating harms in clinical trials: dot plots, stacked bar charts, volcano plots, heat maps, treemaps, and tendril plots. Based on expert assessment, the dot plot and volcano plot were the most preferred approaches for presenting overall summaries of harms, while the tendril plot was considered the least preferred because of its complexity and difficulty of interpretation. The study also clarified the trade-offs among visualization types. Dot plots were useful for presenting detailed comparative information, volcano plots were useful for highlighting possible signals, treemaps supported a broader hierarchical overview but lacked precision, and heat maps could become difficult to interpret when too much information was encoded in a single display.

Other guidance papers addressed visual analytics as part of safety review workflows. Wang et al. [43] provided guidance on using interactive visual analytics to support clinical trial drug safety assessment. The authors distinguished between general safety review and the review of prespecified safety topics of interest. For general safety review, they recommended beginning with displays that rank adverse events according to the strength of evidence for treatment differences, which would allow reviewers to identify events requiring further scrutiny. Interactive features such as tooltips, filtering, zooming, drill-down, onset and duration plots, and graphical patient profiles were described as mechanisms for moving from summary-level patterns to patient-level evidence. For safety topics of interest, the authors recommended tailored displays designed around specific clinical questions, rather than generic summary graphics. The authors also highlighted implementation challenges, including software selection, infrastructure, user training, statistical validation of tools, and the difficulty of sharing interactive displays across organizations and regulatory settings.

Hughes et al. [44] considered visualization in the broader context of structured benefit–risk assessment. Based on benefit–risk case studies, two representations were identified as fundamental across case studies: value trees and effects tables. Value trees helped organize favorable and unfavorable effects into a hierarchical structure, supporting understanding of the decision problem and facilitating preference elicitation. Effects tables summarized outcome metrics for benefits and risks across comparators, helping assessors identify whether further quantitative modeling or preference-based analysis was needed.

Suh et al. [45] addressed the challenge of communicating the performance of regression models used in pharmacovigilance. The authors noted that predictive models may support pharmacovigilance tasks such as identifying underreporting of adverse events, but their adoption depends on whether stakeholders can understand their limitations, reliability, and risk profile. Based on interviews with data scientists and subject matter experts in a pharmaceutical organization, the study found that data scientists tended to prioritize performance metrics, feature distributions, correlations, and data quality, whereas subject matter experts were more concerned with where the model might fail and what risks those failures could introduce into safety-related decisions. The paper therefore argued that aggregate metrics alone are insufficient for communicating model performance in pharmacovigilance. Instead, visual communication should help users inspect model behavior, understand errors, evaluate limitations, and connect model outputs to the practical consequences of clinical safety work.

3.2.4. Scientific Reporting Studies

The seven remaining studies used visualization primarily as a reporting mechanism within broader pharmacovigilance analyses. In these papers, visualizations served to summarize analytical outputs, communicate complex safety-related findings, and support

the interpretation of patterns identified through statistical modeling, data mining, NLP, network analysis, and machine learning approaches.

Several studies used visualization to report findings from signal detection or association-mining analyses. Du et al. [46] applied frequent itemset mining to electronic medical records to identify high-order drug interactions associated with myopathy and used tree-based graphical representations to communicate the directional contribution of individual drugs within multidrug combinations. Mizuno et al. [47] combined kinase affinity data with adverse event reporting rates from the Japanese Adverse Drug Event Report database and used correlation maps and scatterplots to visualize possible relationships between kinase inhibition and adverse events. Schachterle et al. [48] applied the tree-based scan statistic to longitudinal claims data and used tree/network visualizations to support interpretation of signals of disproportionate recording. Similarly, Miyasaka et al. [49] used a self-organizing map and decision tree analysis to visualize and classify antipsychotic-associated neuroleptic malignant syndrome profiles.

Other studies used visualization to report outputs from computational text-mining, network, or predictive modeling approaches. Allam et al. [50] applied word embeddings and t-distributed stochastic neighbor embedding (t-SNE) visualization to French medical forum posts to explore patterns associated with ADEs. Botsis et al. [51] combined NLP with network analysis to evaluate dose-related safety patterns in post-market reports of rabbit anti-thymocyte globulin, using network visualizations to examine relationships between dose ranges and reported adverse events. Parkinson et al. [52] used clustering and heat map visualizations to examine whether preclinical gastrointestinal observations could help predict drug-induced nausea in patients.

3.3. System Design Studies

Forty-one studies from the final pool of included studies designed either a visual analytics system or an interactive visualization system. For the purposes of this review, we distinguished between these two categories based on whether the system incorporated an analytic engine. We defined an interactive visualization system as a system that allowed users to visually explore, filter, query, compare, or drill down into pharmacovigilance-related data through interactive graphical representations but did not include a substantial computational analysis component beyond data retrieval, aggregation, or visual encoding. By contrast, we defined a visual analytics system as a system that combined interactive visualization with an embedded analytic engine, such as statistical modeling, disproportionality analysis, clustering, association rule mining, machine learning, NLP, ontology-based reasoning, semantic search, knowledge representation, signal detection algorithms, or other computational methods. Figure 7 depicts an overview of these systems.

3.3.1. Summary of Studies

In this section, we have provided a summary of the included studies according to the type of system they designed.

Interactive Visualization Systems

Several studies developed interactive systems to support the exploration and review of ADE and medication safety data. Buchanan et al. [53] developed Hepatic Explorer, an open-source interactive system for evaluating potential drug-induced liver injury in clinical trials. The system extends the traditional eDISH plot by allowing reviewers to filter trial participants, inspect quadrant-level liver safety patterns, and drill down from population-level summaries to individual patient laboratory trajectories and clinical narratives. Similarly, Frestel et al. [54] developed a Power BI-based platform for managing pharmacist clinical interventions and medication-related problems. The platform used

multiple interactive dashboards to summarize medication-related problems, pharmacist recommendations, actions taken by healthcare teams, and risk severity, thereby supporting clinical governance and patient safety monitoring.

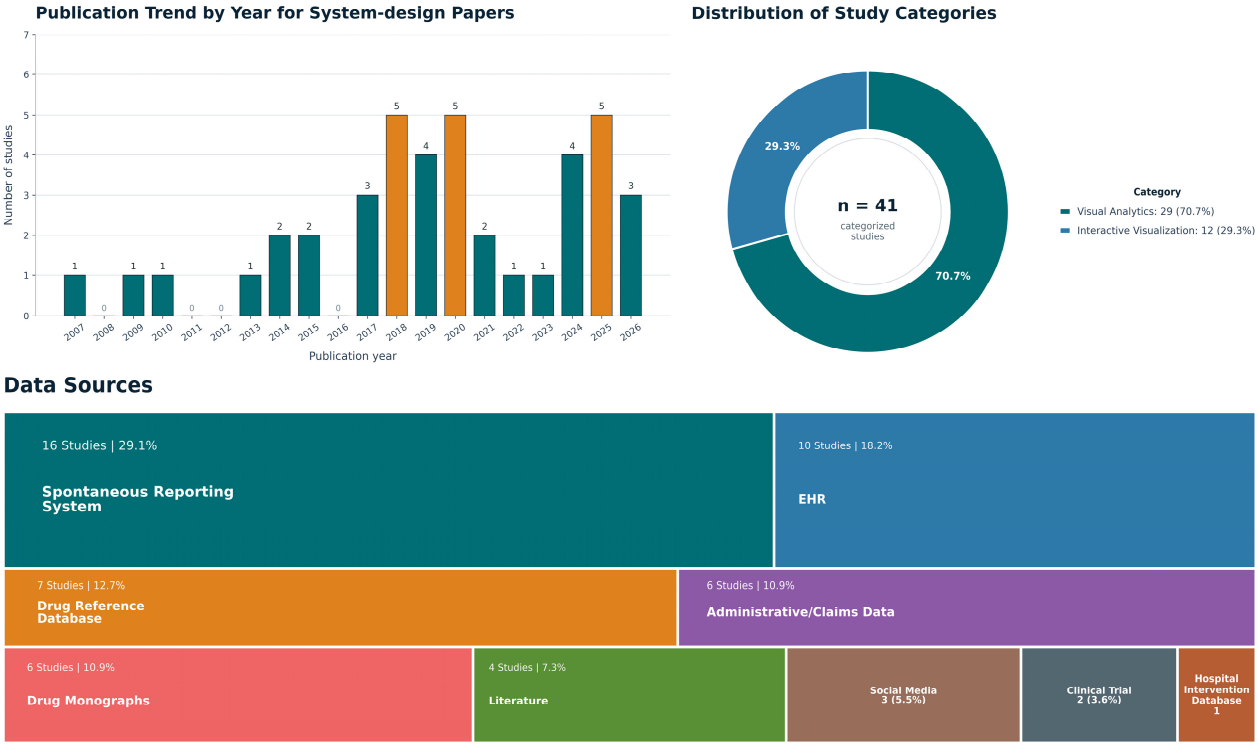

Figure 7. Overview of the system design papers.

Other systems focused on ADE lookup, comparison, and post-market surveillance. Jian-Xiang et al. [55] developed ADRVis, a platform that integrates information from drug instructions with clinically detected ADEs. Its radial link chart visually distinguishes adverse reactions documented in drug instructions, reactions detected in clinical data, and reactions appearing in both sources, helping users identify potentially undocumented risks. Saint-Dizier et al. [56] developed PharmacoExplorer to support the reuse of adverse effect reports from the French National Agency of Medicines. The system allowed users to compare psychotropic drugs, examine adverse event ratios, and explore reported adverse effects through interactive visual displays rather than relying on isolated molecule-level queries.

Several studies addressed medication safety in clinical practice and prescribing contexts. Yang et al. [57] developed the Seoul National University Hospital (SNUH) Common data model (CDM) Drug Prescription Dashboard using diagnostic and prescription data standardized through the OMOP common data model. The system supported conditional drug searches, prescription trend analysis, patient-level review, and polypharmacy exploration. Williams et al. [58] developed SMASH, the Salford Medication Safety Dashboard, to monitor potentially hazardous prescribing in primary care. The dashboard provided practice-level benchmarking, visual performance summaries, and drill-down access to lists of affected patients, supporting targeted prescribing safety interventions. Reddy et al. [59] developed a web-based platform for ADE causality assessment that enables users to submit clinical information, apply WHO-UMC causality categories, and manage review workflows through role-based dashboards.

A group of systems focused on drug interaction, diet–drug interaction, and medication information communication. Hong et al. [60] developed DDID, a web-based resource for

exploring diet–drug interactions, including food–drug and herb–drug interactions. The system provided searchable interaction records, categorized interaction effects, and visual representations of relationships between foods, herbs, drugs, and interaction evidence. Shoshi et al. [61] developed GraphSAW, a web-based system that integrates pharmaceutical and molecular data to support graphical analysis of drug interactions and side effects. Its radial network interface enabled users to explore relationships among drugs, molecules, pathways, and adverse effects. Roosan et al. [62] developed a mobile medication information prototype that used interactive infographics, animations, and human factor design principles to improve patient understanding of medication instructions, warnings, dosage, and storage information.

Two systems focused specifically on temporal and data-quality exploration. Ledieu et al. [63] developed a web-based timeline representation of clinical data to support pharmacovigilance experts in reviewing potential relationships between drug exposures and adverse events. The system organized heterogeneous EHR data chronologically and allowed users to inspect prescriptions, laboratory values, medical codes, and textual records across time. Sharifi Kia et al. [16] developed IRVINE, an interactive visualization system for exploring missing data in spontaneous reporting system databases. The system supported analysis of missingness in FAERS and Canada Vigilance through geographic views, radial summaries, detailed demographic and report-level breakdowns, temporal views, and side-by-side database comparisons.

Visual Analytics Systems

These systems were characterized by a stronger integration of computational analysis with interactive visual exploration. Unlike systems that primarily supported navigation, filtering, or lookup, these tools embedded analytic engines that transformed heterogeneous pharmacovigilance data into candidate signals, structured safety profiles, ranked associations, or machine-readable concepts before presenting them to users. These systems therefore positioned visualization not only as a display layer but also as a mechanism for interrogating, validating, and refining computationally generated safety evidence.

Several systems focused on drug safety profiling, medication review, and clinical decision support. Lamy et al. [64] developed a semantic mining system for adverse events in clinical trials, mapping trial data to Medical Dictionary for Regulatory Activities (MedDRA) and Chemical Entities of Biological Interest (ChEBI) concepts and presenting drug–event probabilities through a matrix view in which flower glyphs summarized adverse event probabilities and affected physiological systems. Similarly, Lamy et al. [65] designed an ontology-based visual analytics website for comparing new drugs, using rainbow boxes, dynamic tables, bar charts, and medical icons to support side-by-side comparison of adverse effects, contraindications, efficacy, interactions, price, and dosage characteristics. Mouazer et al. [66] developed ABiMed, which combined rule-based reasoning and ontology-based patient modeling with radial interaction graphs, traffic-light indicators, posology tables, and adverse effect flower glyphs. These visualizations allowed clinicians to compare current and proposed treatments and inspect whether medication-review recommendations introduced new interaction or adverse effect risks. Duke et al. [67] developed Rxplore to review potential adverse effects in polypharmacy and rank them using a frequency scoring system, using dynamically updated horizontal bar charts to summarize cumulative adverse reaction profiles as medications were added or removed.

A large group of systems supported post-market signal detection and management using spontaneous reporting systems, literature sources, or integrated safety repositories. Gao et al. [68] developed a system for automatic causality assessment of ADE reports. The analytical engine used ordinal logistic regression to predict causality categories and gener-

ated warning signals that captured both event severity and disagreement between reporter and model assessments. These outputs were visualized using a parallel coordinates plot, where each report was represented as a polyline crossing axes such as patient characteristics, reporter assessment, model prediction, and warning signal. Users could brush selected axes to isolate reports with specific patterns, such as strong disagreement between human and algorithmic assessment. A linked table below the visualization provided detailed report information and allowed reviewers to inspect and update assessments.

Yu et al. [69] developed a FAERS-based visualization platform for ADE query and analysis, using severe skin adverse reactions caused by sulfonylureas as an example. The platform supported multi-condition querying by variables such as patient age, gender, event date, reporter occupation, drug name, adverse reaction term, and drug action code. It also allowed users to perform disproportionality analysis. The visualization interface summarized query results using interactive charts showing distributions of patient demographics, reporting outcomes, drug characteristics, and adverse reaction patterns.

Kotowicz et al. [70] developed an interactive dashboard for drug safety surveillance using FAERS data. The system incorporated disproportionality analysis so that users could distinguish statistically related adverse events from reports that were merely frequent. The dashboard was organized into overview and detail sections. The overview section used histograms to show commonly reported adverse events and line charts to display temporal reporting trends. The detail section provided demographic charts, reporter-occupation summaries, and geographic heat maps. This design allowed users to move from a broad view of reporting patterns to more specific inspection of patient, reporter, temporal, and spatial characteristics.

Mittelstädt et al. [71] developed an advanced visual analytics interface for ADE detection in FAERS. The system focused on identifying low-frequency but clinically meaningful drug reaction associations that might be missed by conventional threshold-based methods. It combined relevance filtering, adapted odds ratio measures, and interactive expert validation. The interface included treemaps for overview-level exploration of the drug and adverse event space, alongside a pixel-based display in which the x-axis represented drugs and the y-axis represented adverse reactions. In the pixel-based view, each pixel corresponded to a drug reaction event, color encoded patient outcome severity, and statistically significant signals were highlighted with circular markers.

Yang et al. [72] developed VisDrugs, a web-based visual analytics platform designed to make FAERS data more accessible for researchers and healthcare professionals without requiring advanced bioinformatics expertise. The system processed single-drug adverse reaction reports from FAERS and standardized adverse event terminology using MedDRA preferred terms. Visually, the platform used pie charts to provide an immediate overview of the most frequently reported adverse reactions for a selected drug, allowing users to quickly identify dominant safety concerns. It also generated forest plots to present reporting odds ratios and confidence intervals for drug–event associations, enabling users to assess both the direction and statistical strength of potential signals. By combining simple frequency-based summaries with more formal disproportionality visualization, VisDrugs supported both exploratory review and comparative interpretation of drug safety profiles.

Almenoff et al. [73] developed Online Signal Management, a visual analytics platform intended to improve the efficiency of post-market signal management workflows. The system combined traditional case review with quantitative signal detection by calculating Empirical Bayes Geometric Mean scores for drug–event associations. These scores were presented through interactive treemaps and heat maps, where color intensity helped distinguish stronger signals from weaker or lower-priority associations. The visual interface

allowed safety evaluators to move from broad overviews of signal patterns to more focused examination of specific drug–event pairs.

Spiker et al. [74] developed InfoViP, a post-market surveillance decision support system designed for United States Food and Drug Administration (FDA) safety evaluators who need to review evidence distributed across multiple sources. The platform integrated FAERS spontaneous reports, DailyMed product labeling, and PubMed biomedical literature into a unified interface. Its visualization component used interactive bubble-chart overviews to summarize adverse event patterns for a selected drug, with visual encodings that helped users distinguish events already documented in product labeling from potentially unlabeled events. By linking report-based signals with label information and literature evidence, InfoViP helped evaluators determine whether an adverse event was known, emerging, or in need of further investigation. The system also incorporated NLP to extract clinical concepts from free-text narratives, which made the visual summaries more useful for triaging large volumes of post-market safety data.

Other systems expanded pharmacovigilance beyond traditional spontaneous reports by mining unstructured text, patient-generated content, and scientific literature. Sorbello et al. [75] developed PEARL, a web-based prototype for literature-based pharmacovigilance. The system extracted MeSH terms from PubMed/MEDLINE records and calculated disproportionality measures such as Relative Reporting Ratio and Proportional Reporting Ratio for drug–event associations. Its interface was organized into multiple tabs, each supporting a different analytic perspective. Bar charts summarized the top safety signals for a selected drug, while pie charts showed the distribution of publication types. Treemaps and heat maps supported multidimensional exploration of drug–event associations, and time-course graphs showed how literature-based signals changed over time. This allowed regulatory reviewers to examine both the magnitude and temporal development of literature-derived safety evidence.

Si Li et al. [76] developed a visual analytics framework for exploring adverse reactions to diabetes medications using social media and FAERS data. The system collected patient reviews from AskaPatient and processed FAERS reports, then applied text-mining methods to identify adverse reaction terms in patient comments. The visualization component presented patient posts alongside demographic summaries, medication ratings, reasons for drug use, and adverse reaction frequencies over time. Users could filter by demographic groups or specific side effects and examine temporal variation in patient-reported reactions.

Karapetiantz et al. [77] developed PHARES, an interactive pipeline for monitoring ADEs in web forums and patient portals. The system applied dictionary-based NLP to identify drugs and adverse events in informal patient-generated text, normalizing drugs to Anatomical Therapeutic Chemical (ATC) categories and reactions to MedDRA terminology. Its interface included a control sidebar for filtering by source, time period, drug category, and adverse event category. The dashboard used pie charts to show forum distributions, line charts to display temporal trends in drug and adverse event mentions, histograms to summarize MedDRA categories, and annotation plots to inspect extracted drug–event mentions.

Nishiyama et al. [78] developed a pharmacovigilance platform for monitoring over-the-counter (OTC) drug misuse in Japanese social media data. The system used fine-tuned Japanese Bidirectional Encoder Representations from Transformers (BERT) models trained on labeled tweets to identify patterns of inappropriate drug use, such as overuse. Its visualization component summarized detected misuse patterns by drug category and over time. This allowed researchers and health authorities to identify which OTC drugs were most frequently associated with misuse and when these patterns intensified.

Bobrov et al. [79] developed DrugWatch, a multi-source visual analytics platform for drug safety information. The system integrated FAERS, PubMed, and user-provided text data, while NLP and machine learning supported information extraction and annotation. Its interface included interactive bar charts for demographic and frequency analysis, allowing users to explore adverse event counts by age, sex, and other report characteristics. DrugWatch also included a text annotation interface in which clinical entities such as drugs and side effects were highlighted using color-coded labels. This combination of statistical summaries and annotated text views supported both structured data exploration and detailed review of clinical narratives.

Fong et al. [80] developed a visual analytics approach for medication event review committees by integrating NLP with clinical expert review. The system used machine learning classifiers, including random forest and support vector machine models, to categorize free-text patient safety reports into medication error types. Its dashboard presented the resulting categories through bar charts that summarized the frequency of error types such as dispensing errors, pharmacy delivery delays, and prescriber errors.

Several visual analytics systems were designed specifically for drug–drug interaction, multidrug adverse reaction, and medication error analysis. Kakar et al. [15] developed DIVA to support the exploration and validation of hypothesized drug–drug interaction signals. The system used an Augmented Interaction Model to connect machine-generated signals with contextual information such as adverse reaction severity and whether an interaction was already known. Its interface included several coordinated views. A screening view used a node-link diagram to show candidate drug–drug interactions, with visual encodings for signal interestingness and known or unknown status. A triage view used small multiples to support drug-centered comparison, while a forensic view used a hierarchical tree layout to inspect the full interaction profile of a selected drug.

Kakar et al. [81] also designed DEVES, an interactive visual analytics system for discovering unexpected drug–drug interaction-related adverse event signals in spontaneous reporting data. The analytical engine mined candidate interaction signals and ranked them using a significance score. The system also incorporated external domain knowledge to distinguish potentially novel signals from already known adverse events or established drug interactions. Its visual interface supported the triaging of ranked signals and helped analysts compare statistical mining results with existing biomedical knowledge.

In another study, Kakar et al. [82] developed MEV, a visual analytics system for medication error detection using FAERS reports. The system combined structured report fields with rule-based NLP applied to unstructured narratives. Its interface used multilayer treemaps to display medication error reports by categories such as error type, drug name, error stage, and error cause. Rectangle size encoded report counts, while color represented severe outcomes or severity-related measures. A temporal area chart supported brushing and zooming over time, and demographic bar charts displayed distributions by sex, age, location, and reporter occupation. A linked report view allowed analysts to move from aggregate error patterns to individual case narratives.

Qin et al. [83] developed MeDIAR, a visual analytics platform for detecting and validating multidrug adverse reactions. The system used rule-driven learning to identify non-spurious drug interaction signals from large-scale spontaneous reporting data and prioritized them using contextual association clusters. Its main visualization used a network view in which drugs were represented as nodes and interactions as edges, with edge width encoding the strength of the calculated contrast score. The interface also used specialized glyphs to represent statistical confidence and contextual association information.

Yao et al. [84] developed the High-Order DDI Explorer (Figure 8), a visual analytics system for estimating and visualizing directional drug–drug interaction effects involving

higher-order (more than one) drug combinations. The system used FAERS data and applied frequent itemset mining to identify relevant drug combinations associated with myopathy-related adverse events. It then calculated odds ratios to estimate how the risk of an adverse event changed when an additional drug was added to an existing baseline combination. Its main visualization used an interactive sunburst diagram in which nested rings represented drug subsets of increasing order, allowing users to trace directional interaction pathways from smaller to larger drug combinations. Within the sunburst, color encoded the magnitude of the odds ratio, helping users identify combinations associated with increased or decreased adverse event risk.

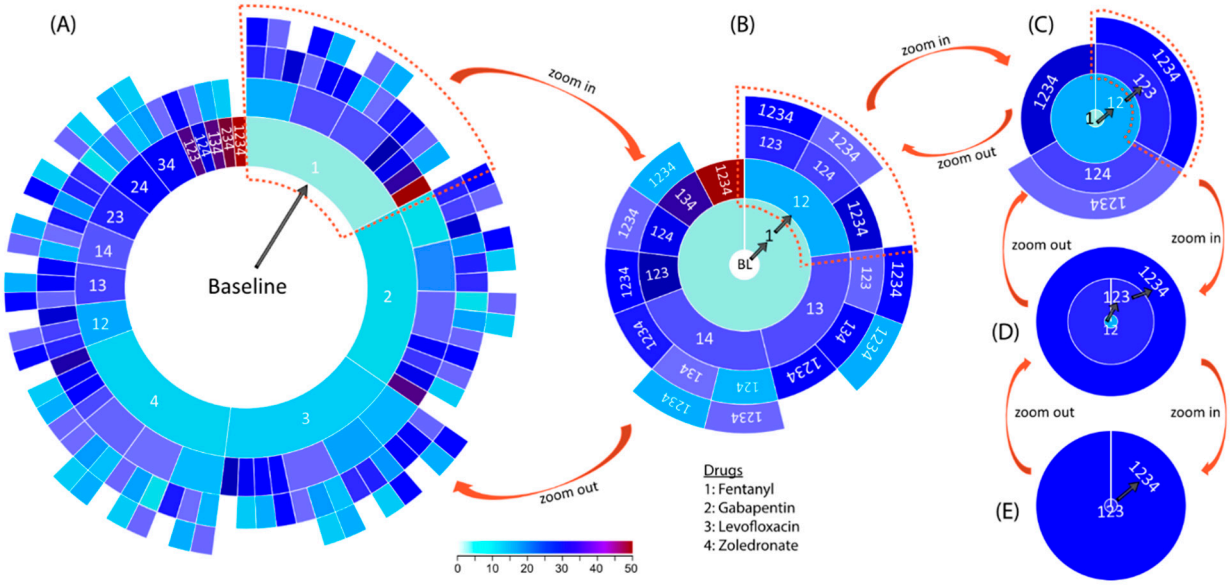

Figure 8. High-Order DDI Explorer showing (**A**) the overall directional interaction landscape and (**B**–**E**) progressive zooming from the baseline drug to higher-order combinations with multiple drugs. Sector color encodes the magnitude of the drug–drug interaction effect. Source: Image by Yao et al. [84].

A further set of systems emphasized EHRs, hospital safety data, prescribing behavior, and methodological evaluation. Ledieu et al. [85] developed two complementary time-oriented visual analytics applications for pharmacovigilance. The Timeline interface presented heterogeneous patient-level EHR data chronologically, combining prescriptions, diagnoses, laboratory values, and clinical notes. It used Visualization of Concepts in Medicine (VCM) medical icons to represent clinical concepts and line charts to display laboratory trends, helping reviewers examine whether adverse events occurred in temporal proximity to drug exposures. The Sequence Analyzer supported cohort-level exploration by allowing users to define a reference sequence, such as a drug exposure followed by an abnormal laboratory result, and search for similar sequences across patients. Visual event sequences were represented using distinct shapes, while approximate matching algorithms helped identify temporally related patterns that might otherwise be difficult to detect manually.

Abdullah et al. [86] developed VISA_M3R3 to identify medications and medication combinations associated with acute kidney injury using electronic medical records. The analytical backend combined multivariable logistic regression with Eclat frequent itemset mining, allowing the system to detect both individual medication risks and higher-order medication combinations. The interface used coordinated visual views to help users inspect the underlying data, adjust analytic parameters, filter records, and examine results from regression and itemset-mining analyses.

In another study, Abdullah et al. [87] developed VALENCIA, a visual analytics system for dimension reduction and cluster analysis of high-dimensional EHRs. The system addressed the challenge of selecting appropriate dimension-reduction and clustering methods for complex clinical datasets. Its interface allowed users to select variables, configure analytic methods, run alternative models, and visually compare their outputs. Coordinated views supported iterative movement between data overview, dimension reduction, clustering, and interpretation.

Hu et al. [88] developed a network-based visual analytics framework for opioid prescribing data. The system transformed prescription records into a dynamic bipartite network linking patients and prescribers over time. This representation made it possible to detect patterns such as patients receiving opioids from multiple prescribers or unusual prescribing clusters. The visual analytics component included global network views that summarized structural patterns across the dataset and local views that allowed analysts to inspect specific patient–prescriber subgraphs over time. By using network visualization, the system exposed relational prescribing patterns that would be difficult to identify from conventional tabular summaries.

Simpao et al. [89] developed a visual analytics dashboard to optimize drug–drug interaction alert rules in a pediatric hospital's EHR system. The system was designed to reduce alert fatigue by helping administrators identify alerts that were frequent, overridden, or clinically less useful. On the dashboard's interface, line graphs coupled with tabular displays were used to summarize alert frequencies, override patterns, and distributions of alert-related measures, allowing users to examine alert burden across medications, rules, and clinical contexts.

Băceanu et al. [90] developed Expert Explorer, a web-based system for validating ADE detection rules in hospital data. The system used association-rule mining to generate candidate safety rules and then allowed clinical experts to inspect both the rules and the hospital stays matching them. Its interface combined structured tables, line charts, configurable dashboards, and expert review forms. These components supported a rule-validation workflow in which clinicians could confirm, reject, or refine algorithmically generated rules.

Xiaochun Li et al. [91] developed a statistical visualization tool for assessing the performance of safety surveillance methods in electronic healthcare databases. The system was created in the context of OMOP and focused on comparing analytical methods and parameter settings for active drug safety surveillance. It calculated performance metrics such as sensitivity, specificity, area under the curve, and mean average precision. These results were visualized using heat maps and hierarchical clustering, allowing users to compare method performance across large parameter spaces and patient subgroups.

3.3.2. Supported Pharmacovigilance Activities

Signal management was the most frequently supported activity, appearing in 30 systems. These systems supported the identification, assessment, prioritization, and further investigation of potential drug-related safety concerns using spontaneous reports, clinical records, scientific literature, and other safety-related data sources. Case management was supported by 11 systems, which primarily facilitated the review, assessment, classification, and management of individual adverse event reports or patient-level safety information. Benefit–risk management was supported by nine systems and generally involved comparing medications or treatment alternatives, characterizing risks, assisting medication-related decisions, and supporting risk-minimization activities.

At the task level, the systems supported distinct operational components within the broader pharmacovigilance activities. Twenty-one systems specifically supported the iden-

tification, assessment, prioritization, or validation of potential safety signals. Other systems classified under signal management contributed through related tasks rather than direct signal detection. Evidence review, exploration, and knowledge synthesis were supported by 14 systems, which enabled users to examine and integrate information from adverse event reports, clinical records, drug monographs, and scientific literature. Decision support was addressed by 11 systems through functions such as medication review, prescribing safety evaluation, treatment comparison, and signal prioritization. Nine systems supported case review by facilitating detailed examination of individual reports, patient histories, medication timelines, laboratory findings, and clinical narratives, while eight systems supported risk characterization and comparative safety by enabling comparisons across medications, treatments, populations, or adverse event profiles. More specialized tasks included medication error and misuse monitoring in five systems, evaluation of surveillance methods or detection rules in four systems, safety data quality and reporting in three systems, and safety information communication in two systems.

3.3.3. Visualizations Employed

Plots and charts were the most frequently employed visualization category, appearing in 31 systems. Bar charts were particularly common and were generally used to compare frequencies or summarize the distribution of drugs, adverse events, patient characteristics, medication errors, and signal measures. Line charts and other time-oriented plots were frequently used to represent changes in reporting patterns, medication use, laboratory measurements, safety signals, and clinical events over time.

Graphs, trees, and networks were used in 11 systems. These representations were particularly suited to displaying relationships among drugs, adverse events, drug interactions, clinical concepts, pathways, and reports. Node-link and radial network representations were used to expose relational structures, while tree-based and hierarchical representations supported the examination of multidrug interactions, safety classifications, and relationships at different levels of detail. Flow-oriented diagrams were also used to represent connections or transitions among clinical and pharmacovigilance entities.

Glyphs and multidimensional icons were employed in 10 systems. These representations integrated several safety-related attributes into compact visual objects and were used to summarize multidimensional drug profiles, adverse event probabilities, clinical characteristics, signal properties, and medication-related warnings. Examples included flower glyphs, medical icons, and other composite visual forms in which multiple properties were encoded through combinations of size, color, shape, and position.

Enclosure diagrams appeared in eight systems. Treemaps were the most common representation in this category and were used to organize large collections of drugs, adverse events, medication errors, or safety signals into hierarchical or grouped structures. Sunburst diagrams and Venn diagrams were used similarly but less frequently in the studies.

Maps were employed in seven systems, predominantly in the form of heat maps. Heat maps were used to display the strength, frequency, or statistical relevance of drug–event associations and to facilitate comparison across large matrices of medications, adverse events, analytical methods, or patient characteristics. Geographic representations were rarely utilized; for instance, in one study, a choropleth map was used to show differences in reporting contributions or data-quality patterns across locations.

3.3.4. Interaction Capabilities

The 41 reviewed systems supported a broad range of interaction capabilities for exploring and examining pharmacovigilance information. Selecting was the most common interaction, supported by 33 systems. This enabled users to focus on individual drugs,

adverse events, reports, patients, or signals and commonly served as the initial action for accessing further information or modifying other views.

Filtering was supported by 29 systems and was the second most common interaction. Pharmacovigilance systems frequently contain large numbers of reports, drug–event combinations, clinical records, and safety measures. Filtering allowed users to reduce this information according to criteria such as medications, adverse events, patient demographics, reporting periods, seriousness, outcomes, report sources, or signal strengths, playing an important role in moving from broad safety overviews to subsets relevant to a particular clinical or regulatory question.

Drilling was supported by 21 systems. It allowed users to reveal information that was not initially visible and to move from aggregated visual summaries to more detailed evidence. This commonly involved progressing from an overview of a signal or reporting pattern to an individual adverse event report, patient history, laboratory trajectory, clinical narrative, or drug–event association. Searching was supported by 18 systems and enabled users to locate particular drugs, adverse events, reports, clinical concepts, interactions, or literature records within a large body of information.

Navigating was supported by 14 systems. It facilitated movement among dashboards, interface modules, analytical perspectives, temporal views, hierarchical levels, and case-level displays. This was particularly important in systems that organized pharmacovigilance information across several complementary views. Comparing was supported by eight systems and allowed users to examine similarities and differences among medications, treatments, patient groups, reporting databases, time periods, safety profiles, or analytical results. Storing and retrieving, also supported by eight systems, enabled the preservation and subsequent access of reports or summaries of analysis.

Other interaction capabilities were less frequently supported. Zooming appeared in six systems, while arranging appeared in five systems. Translating and sorting were each supported by four systems, and annotating appeared in three systems. Linking was identified in only two systems, and sharing was the least common interaction and was reported in only one system. Two studies did not provide sufficient information regarding the interaction capabilities of their systems. Figure 9 provides an overview of the characteristics of the systems with regard to the supported pharmacovigilance activity/task, visualizations, and interactions.

3.3.5. Analytical Methods and Computational Components

A range of analytic methods was integrated into the visual analytics systems to support the detection, assessment, and exploration of pharmacovigilance evidence. These methods were grouped into ten categories: (1) text mining and NLP, (2) statistical signal analysis, (3) pattern discovery, (4) regression, (5) ontological and semantic analysis, (6) classification, (7) network analysis, (8) anomaly detection, (9) dimensionality reduction, and (10) clustering. Because several systems incorporated more than one analytic method, a single system could be assigned to multiple categories. Text mining and NLP was the most frequently represented category, with 11 mentions (28.2%), followed by statistical signal analysis with eight mentions (20.5%), pattern discovery with six mentions (15.4%), and regression with four mentions (10.3%). Ontological and semantic analysis and classification each accounted for three mentions (7.7%), while network analysis, anomaly detection, dimensionality reduction, and clustering were each identified once (2.6%). Figure 10 depicts the distribution of the analytical methods utilized across the 29 visual analytics systems included in this study.

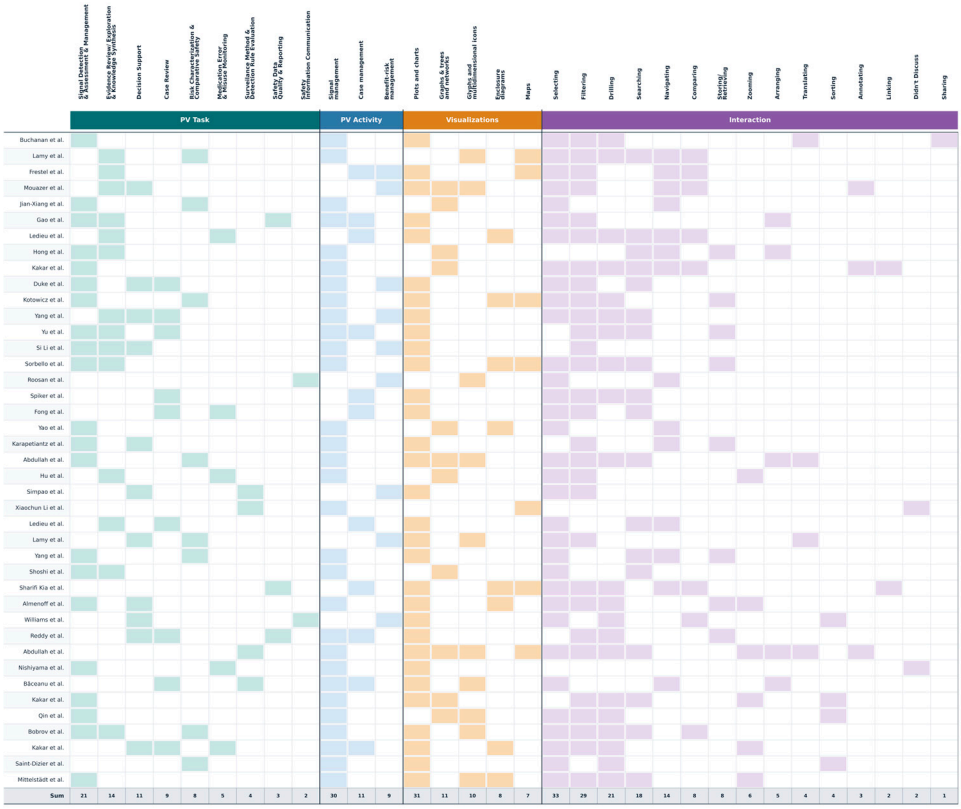

Figure 9. Overview of the characteristics of the systems with respect to pharmacovigilance activity/task, visualizations employed and possible interactions [15,16,52–90].

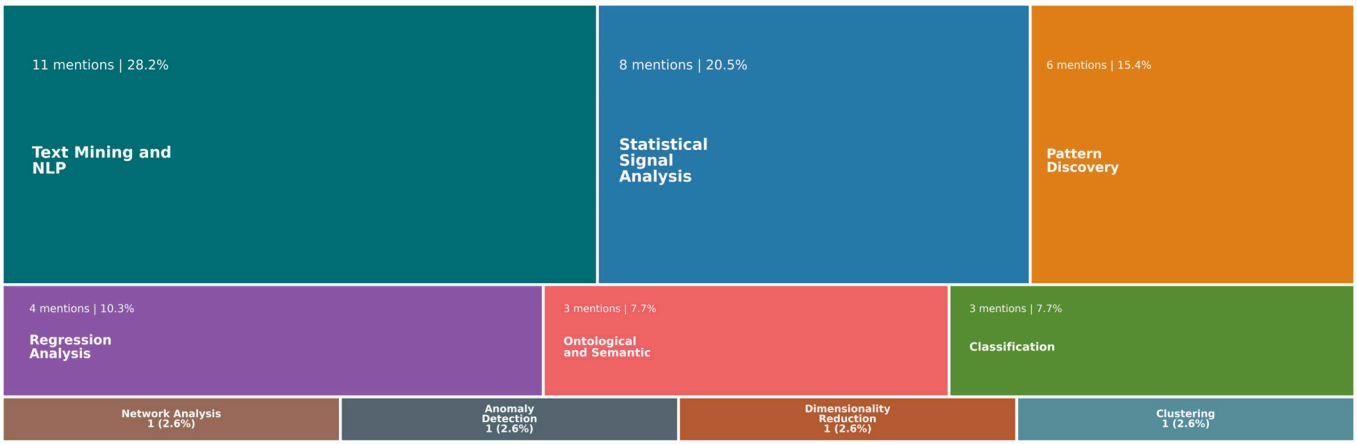

Figure 10. Distribution of analytical methods utilized across visual analytics studies.

Text mining and natural language processing: Text-mining and NLP methods transform unstructured or semi-structured textual information into structured representations that can be analyzed and visualized [92]. Pharmacovigilance data frequently contain free-text narratives, including spontaneous report descriptions, patient safety reports, clinical notes, biomedical literature, and social media posts [92]. Text-mining methods can be used to identify mentions of drugs, adverse events, medication errors, indications, and other clinically relevant entities. Subsequent processing may normalize these entities to controlled terminologies, determine relationships between them, or assign the documents to predefined categories. For example, MEV uses rule-based named-entity recognition to extract and standardize relevant information from the narrative portions of medication error reports before presenting the extracted entities through coordinated

visualizations [82]. PHARES applies an NLP pipeline to identify drugs and adverse events in French web-forum posts and normalize them using the Anatomical Therapeutic Chemical (ATC) and MedDRA terminologies [77]. Similarly, Nishiyama et al. [78] employs a fine-tuned Japanese BERT model to identify patterns of over-the-counter medication misuse in user-generated social media content.

Statistical signal analysis: Statistical signal analysis refers to the quantitative identification and prioritization of potential associations between medicinal products and adverse events. In pharmacovigilance, these methods are commonly used to determine whether a particular drug–event combination is reported more frequently or displays a stronger association than would otherwise be expected. These methods generally calculate a numerical measure for each drug–event combination, which can subsequently be filtered, compared, ranked, and visually examined by safety reviewers [93,94]. For example, VisDrugs integrates disproportionality analysis to identify the most prominent reported reactions for selected drugs and to support comparisons between the reaction profiles of multiple products [72]. PEARL extends statistical signal analysis to the biomedical literature by generating candidate drug–event pairs from MeSH-indexed PubMed records and applying disproportionality measures to identify potentially relevant literature-based signals [75].

Pattern discovery: Pattern discovery methods are used to identify recurring combinations, associations, rules, or temporal sequences within pharmacovigilance and clinical data. These methods are particularly useful when the number of possible relationships among drugs, adverse events, diagnoses, and patient characteristics is too large to examine manually. Pattern discovery can include frequent itemset mining, association-rule learning, sequential-pattern mining, sequence alignment, and rule-learning methods [95,96]. Frequent itemset mining identifies groups of items that repeatedly occur together, whereas association-rule learning derives directional relationships between such items [97]. Sequential-pattern mining extends this process by considering the order in which clinical events occur [98]. For example, Sequence Analyzer integrates a modified Smith–Waterman algorithm to identify patient event sequences that are similar to a user-defined reference sequence. It also uses Apriori and Generalized Sequential Pattern (GSP) algorithms to identify frequent associations and common temporal sequences within a patient cohort [85]. Yao et al. [84] use the Apriori algorithm to mine high-order directional drug interactions involving combinations of more than three drugs and visually organize the resulting interaction patterns. DEVES uses a rule-learning-based mining algorithm to generate and rank drug-interaction adverse event signals, after which analysts can visually examine the supporting reports and contextual evidence [81].

Regression: Regression methods estimate relationships between an outcome variable and one or more variables. In pharmacovigilance visual analytics, regression models were used for causality assessment, medication risk estimation, and examination of the effects of analytic parameters on surveillance performance [99]. For example, Gao et al. [68] developed an automatic causality assessment model based on ordinal logistic regression. The model predicts one of five ordered causality-assessment categories for each ADE report. Its predictions are subsequently used to calculate a warning score, and the interactive interface enables reviewers to compare model-generated assessments with assessments provided by reporters and pharmacovigilance experts. VISA_M3R3 combines multivariable logistic regression with frequent itemset mining to identify individual medications and medication combinations associated with an increased risk of acute kidney injury [86].

Ontological and semantic analysis: Ontological and semantic methods formally represent domain entities and the relationships among them. These entities may include medicinal products, adverse events, clinical trials, patient characteristics, treatments, and outcomes. Ontologies and semantic models can support the integration of heterogeneous data,

queries at different levels of granularity, terminology alignment, and exploration of related concepts [100]. For example, ABiMed combines multilingual contextual embeddings with an ontological patient model based on the Observational Medical Outcomes Partnership (OMOP) common data model to integrate patient-specific information and contextualized medication knowledge [66]. Lamy et al. [64] developed an ontological model containing information from clinical trials of pain treatments and used semantic-web technologies to query the data at different levels of granularity.

Classification: Classification methods assign observations to predefined categorical labels according to their features [101]. Classification was frequently combined with NLP because the observations being categorized were often textual reports. For example, Fong et al. integrate NLP-based text-classification models with a dashboard to categorize medication-related patient safety reports and facilitate their review by clinical experts and patient safety committees [80]. Similarly, the system developed by Nishiyama et al. [78] classified the identified cases of over-the-counter medication misuse.

Network analysis: Network analysis represents data as interconnected entities, or nodes, linked by relationships, or edges. The resulting graph structure can be analyzed to identify connected groups, highly influential entities, unusual relationships, or changes in interaction patterns over time [102]. Hu et al. [88] model opioid prescribing data as a dynamic bipartite network in which patients and prescribers form two distinct node types connected through prescription relationships. The system constructs annual and monthly networks, calculates connected components and network statistics, and supports exploration of both global prescribing structures and local patient–prescriber relationships.

Anomaly detection: Anomaly detection methods identify observations or patterns that differ substantially from expected behavior. These methods may be used to detect unusual medication utilization, atypical reporting patterns, suspicious prescribing relationships, or other observations that warrant further investigation. Anomalies do not necessarily represent confirmed safety problems; rather, they identify cases that are sufficiently unusual to require expert review [103]. In the opioid prescription monitoring platform developed by Hu et al. [88], anomaly detection is applied to the patient–prescriber network to identify potentially problematic patients and unusual prescribing relationships. The detected observations can then be examined within the global, local, and temporal network visualizations to determine whether the apparent anomaly has a plausible clinical or operational explanation.

Dimensionality reduction: Dimensionality reduction transforms data containing a large number of variables into a smaller set of dimensions while retaining as much of the meaningful structure as possible. These methods can reduce computational complexity and make high-dimensional clinical or pharmacovigilance data more suitable for visual exploration. They can also help analysts identify the principal variables or combinations of variables that differentiate patient groups [104]. VALENCIA integrates multiple dimensionality-reduction techniques into a visual analytics environment for exploring high-dimensional electronic health record data [87]. The system allows users to compare alternative dimensionality-reduction results, interactively adjust analytic settings, and investigate the relationships between the reduced representation and the original clinical variables.

Clustering: Clustering is an unsupervised analytic method that groups observations according to their similarity without requiring predefined class labels [105]. The objective is generally to create groups in which observations within the same cluster are more similar to one another than to observations assigned to other clusters. In clinical and pharmacovigilance applications, clustering can be used to identify patient subgroups, adverse event profiles, medication-utilization patterns, or other latent structures in the data. VALEN-

CIA combines cluster analysis with dimensionality reduction to assist users in exploring high-dimensional EHR data [87].

3.3.6. Evaluation of Systems

From the 41 included systems, 16 (39.0%) reported a formal evaluation, including 12 of the 29 visual analytics systems [15,64–67,70,72–75,82,85] and four of the 12 interactive visualization systems [16,59,62,63]. These evaluations primarily examined usability, perceived usefulness, workflow compatibility, and task efficiency through focus groups, interviews, think-aloud sessions, questionnaires, and task-based studies. In some studies where formal evaluation was not conducted, evaluation was frequently presented through illustrative usage scenarios or real-world case studies demonstrating how systems supported representative analytical tasks and revealed clinically relevant patterns [81,83,86,87]. Some systems were instead assessed using technical or operational evidence, including algorithm performance, recovery of previously known safety signals, analysis of real-world datasets or patient cases, implementation outcomes, and usage statistics. Although these approaches provided evidence of feasibility and practical utility, they did not constitute formal summative user-experience evaluations. As shown in Figure 11, evaluation was infrequent before 2017 and appeared more frequently thereafter, although the annual proportion fluctuated substantially and did not demonstrate a consistent upward trend.

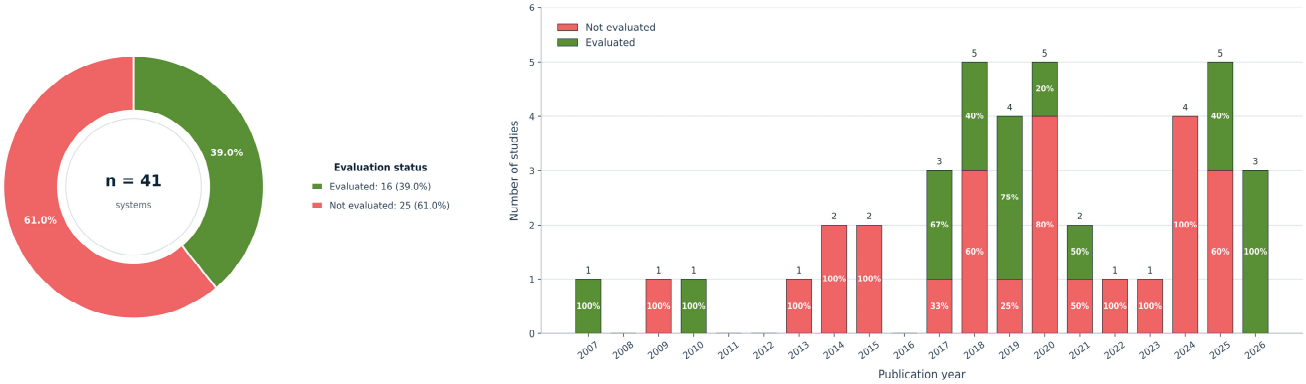

Figure 11. Overall and temporal distributions of evaluation status of systems.

4. Discussion

This scoping review provides a focused synthesis of how visualization and visual analytics have been applied within pharmacovigilance. Among the 67 included studies, 41 described the design of an interactive visualization or visual analytics system, whereas 26 represented non-system research comprising bibliometric and visual analyses, novel visualization designs, methodological guidance, and scientific reporting studies. Signal management was the most frequently supported pharmacovigilance activity, appearing in 30 systems. At the more granular task level, 21 systems directly supported the identification, assessment, prioritization, or validation of potential safety signals. The difference between these figures indicates that not all systems classified under signal management performed signal detection directly; some instead supported related activities such as evidence exploration, signal triage, contextual assessment, or validation. Evidence review and knowledge synthesis, decision support, case review, and comparative risk characterization were also common, whereas medication error monitoring, data-quality assessment, surveillance method evaluation, and safety communication were less frequently addressed.

The reviewed systems used heterogeneous sources of safety information, although spontaneous reporting systems remained the most prominent. Several systems integrated more than one source, which demonstrates the potential of visual analytics to bring to-

gether complementary evidence that would otherwise remain distributed across separate repositories. Nevertheless, the continued prominence of spontaneous reporting data indicates that much of the field remains oriented toward established post-market signal surveillance practices.

Plots and charts were the most frequently used visualization category. These included bar charts, line charts, scatterplots, forest plots, and other conventional displays. Their prevalence suggests that pharmacovigilance systems have prioritized familiar, easily interpretable representations for communicating frequencies, trends, treatment comparisons, and signal measures. This aligns with previous guidance studies recommending conventional displays, such as dot plots, bar charts, and line graphs, because they impose a lower cognitive load on clinical and regulatory users, while more complex visualizations may be difficult to understand [14,41,42]. Glyphs and multidimensional icons provided a complementary approach by integrating multiple safety-related attributes into compact visual forms. Such representations may facilitate rapid recognition of multidimensional drug profiles, signal characteristics, and medication-related warnings. Their effectiveness, however, depends on whether users can interpret the visual encodings and distinguish the attributes presented simultaneously [106,107]. The comparatively limited use of networks, hierarchical displays, multidimensional glyphs, and novel visualizations may limit support for examining relationships among multiple drugs, adverse events, patient characteristics, evidence sources or complex analytical tasks [108]. Accordingly, the findings do not suggest that one visualization category is inherently superior; rather, they reinforce previous recommendations that visual representations should be selected according to the analytical task and data structure [23,109].

The interaction findings indicate a strong emphasis on exploratory analysis, with selecting, filtering, drilling, searching, and navigating as the most frequently supported capabilities. These interactions enabled users to move from aggregated overviews to specific drug–event associations, individual reports, patient histories, laboratory trajectories, and clinical narratives. However, substantially fewer systems supported comparing, linking, annotating, preserving analytical states, or sharing findings. This limitation is important because pharmacovigilance assessment is multidisciplinary and iterative. It involves comparisons across products, populations, databases, periods, and analytical methods, as well as the documentation, discussion, and communication of findings [110,111]. Although existing systems effectively supported individual data inspection, their interaction capabilities provided limited support for maintaining analytical provenance, recording interpretations, reconciling disagreements, or transferring findings between reviewers. Moreover, designers should consider the interactivity (quality of interaction) of the system, as it directly influences how effectively visual analytics systems support analytical tasks [112,113].

The analytical engines incorporated into the 29 visual analytics systems reflected the characteristics of contemporary pharmacovigilance data. Text mining and NLP were the most prevalent, consistent with the large volume of safety evidence embedded in narrative reports, clinical notes, scientific literature, and patient-generated content. Statistical signal analysis was also prominent, which reflects the established role of disproportionality methods in spontaneous report surveillance, while pattern discovery and regression extended analysis to multidrug combinations, temporal sequences, causality assessment, and patient-level risk estimation. Ontological and semantic analysis and classification were also represented. By contrast, clustering, dimensionality reduction, anomaly detection, and network analysis were comparatively uncommon. This suggests that the field has not fully exploited methods for identifying latent population structures, high-dimensional safety profiles, and complex relational patterns. A related limitation was the restricted visibility and

control users had over these analytical engines. Many systems presented model outputs without adequately exposing their assumptions, parameter sensitivity, uncertainty, data limitations, or potential failure conditions. This reflects a broader distinction in EHR visual analytics between merely displaying analytical results and enabling users to inspect and refine the analytical process. Given the consequences of both false-positive and false-negative signals, pharmacovigilance systems should present signal scores alongside uncertainty, supporting evidence, methodological assumptions, and known limitations. This need is reinforced by Suh et al. [45], who found that subject matter experts were concerned not only with overall model performance but also with the conditions under which models fail and the implications of those failures for safety-related decisions.

A major finding concerns the limited maturity of system evaluation. Only 16 of the 41 systems, or 39.0%, reported a formal evaluation. This represents one of the clearest methodological gaps that is consistent with concerns previously identified in health-informatics visual analytics research [114]. Moreover, the available evaluations focused primarily on usability and perceived usefulness. These outcomes are necessary because a system that cannot be understood or integrated into users' workflows is unlikely to be adopted. However, usability alone does not establish analytical validity or decision value. A system may be easy to use while producing misleading interpretations, encouraging overconfidence in weak signals, or failing to improve the decisions made by safety reviewers. Consequently, future systems should complement user experience evaluation with technical accuracy evaluation for more comprehensive results regarding their usability and effectiveness.

This review has several limitations. The restriction to English-language publications resulted in the exclusion of 12 potentially relevant articles at full-text screening. In addition, inconsistent terminology across visualization and pharmacovigilance may also have limited retrieval. Relevant systems may be described as dashboards, exploratory interfaces, visual data-mining tools, safety informatics platforms, or decision support systems, without mentioning visualization or visual analytics. Although broad search terms were used to mitigate this issue, some eligible studies may have been missed. Moreover, the findings were dependent on the level of detail provided in the included publications; consequently, features or procedures that were not reported may still have been present in the implemented systems. Meta-analysis was inappropriate because study objectives, systems, users, datasets, and evaluation methods were highly heterogeneous. Conventional risk-of-bias tools were not applied because most publications described technical or system design research rather than clinical effectiveness studies. The review protocol was not prospectively registered or published because registration was not incorporated into the study plan at the outset. Several included systems were developed by members of the research team, which may have introduced familiarity bias. Although all studies were independently evaluated using the same predefined criteria and procedures, residual bias cannot be excluded.

Future pharmacovigilance visual analytics systems should support complete analytical and decision workflows, extending from signal generation to case review, evidence integration, benefit–risk assessment, communication, and follow-up. This requires linking computational signals to patient-level data, source reports, product information, literature, and alternative explanations while integrating complementary sources such as spontaneous reports, EHRs, claims, clinical trials, and patient-generated data. Systems should make data provenance, completeness, temporal coverage, terminology mappings, uncertainty, model assumptions, and potential biases visible and allow users to inspect and refine analytical processes while maintaining expert oversight of AI outputs. Further comparative evaluations are needed to determine whether specialized visual representations offer

meaningful advantages over simpler charts and whether these benefits justify their greater cognitive demands.

5. Conclusions

In this paper, we conducted a scoping literature review to identify studies describing the use and development of visualization and visual analytics in pharmacovigilance and to provide a comprehensive overview of the field. This review demonstrates the role of analytics, visual representations, and interactive techniques in supporting pharmacovigilance activities and organizes the existing literature using these dimensions. Furthermore, we identified key challenges associated with the design, implementation, and evaluation of pharmacovigilance visual analytics systems. Finally, we highlighted areas that have received limited attention and identified opportunities for future research, including more comprehensive support across pharmacovigilance processes, improved integration of evidence sources, greater transparency of analytical outputs, and more rigorous evaluation of system effectiveness.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/informatics13090147/s1. The data supporting the findings of this study and a completed PRISMA-ScR [115] are available in Supplementary File S1.

Author Contributions: Conceptualization, A.S.K., M.M. and K.S.; Methodology, A.S.K., M.M. and K.S.; Investigation, A.S.K. and M.M.; Original draft preparation, A.S.K.; Review and editing, A.S.K., M.M. and K.S.; Supervision, K.S. All authors have read and agreed to the published version of the manuscript.

Funding: This study has been supported by a grant from the Natural Sciences and Engineering Research Council of Canada (NSERC) (reference number: R3048A01).

Institutional Review Board Statement: Not Applicable.

Informed Consent Statement: Not Applicable.

Data Availability Statement: The original contributions presented in this study are included in the Supplementary File S1. Further inquiries can be directed at the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ADE	Adverse drug event
AI	Artificial intelligence
ATC	Anatomical Therapeutic Chemical
BERT	Bidirectional Encoder Representations from Transformers
CDM	Common data model
ChEBI	Chemical Entities of Biological Interest
DDI	Drug–drug interaction
EDIFICE-AP	Epistemology and Design of Human-Information Interaction in Complex Complex Cognitive Activities–Action Patterns
EHR	Electronic health record
eDISH	Evaluation of drug-induced serious hepatotoxicity
FAERS	FDA Adverse Event Reporting System
FDA	United States Food and Drug Administration
GSP	Generalized Sequential Pattern
MedDRA	Medical Dictionary for Regulatory Activities
MEDLINE	Medical Literature Analysis and Retrieval System Online

MeSH	Medical Subject Headings
NLP	Natural language processing
OMOP	Observational Medical Outcomes Partnership
OTC	Over the counter
PRISMA-ScR	Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
PT	Preferred term
PV	Pharmacovigilance
SNUH	Seoul National University Hospital
t-SNE	t-distributed stochastic neighbor embedding
VCM	Visualization of Concepts in Medicine
NSERC	Natural Sciences and Engineering Research Council of Canada

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