Computational Pharmacovigilance for Herbal and Natural Product Medicines: Signal Detection, Interaction Mapping, Adverse Event Interpretation, and Risk Governance

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ABSTRACT

Herbal and natural product medicines create distinctive pharmacovigilance challenges because safety reports may involve heterogeneous products, uncertain botanical identity, variable preparations, incomplete exposure documentation, co-administered medicines, and patient-reported narratives with missing clinical context. This article proposes an original computational pharmacovigilance framework for safer surveillance of herbal medicines, botanical products, phytochemicals, and natural product preparations. The framework integrates product and exposure identity review, adverse event coding, reporting-quality assessment, duplicate detection, missing-data review, disproportionality screening where supported, text mining, interaction mapping, mechanistic plausibility assessment, causality uncertainty, expert review, risk prioritization, and governance actionability. Its central contribution is to distinguish statistical safety signals from clinical suspicion, mechanistic plausibility, reporting bias, product uncertainty, herb–drug interaction risk, adverse event interpretation, and governance decisions. The proposed model treats computational methods as tools for signal prioritization and evidence organization rather than as independent arbiters of causality, incidence, patient-specific risk, or regulatory action. By linking signal detection to product identity, exposure context, reporting quality, patient vulnerability, co-medication review, causality assessment, uncertainty communication, and feedback loops, the framework supports a more cautious and transparent approach to herbal and natural product medicine safety surveillance.

Key Words: *Computational pharmacovigilance, Herbal medicines, Natural products, Signal detection, Adverse events, Herb–drug interactions*

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INTRODUCTION

Pharmacovigilance for herbal and natural product medicines is complicated by product heterogeneity, incomplete exposure documentation, variable reporting pathways, and uncertainty about whether a reported adverse event reflects a product-related adverse reaction, an interaction, an underlying condition, a reporting artefact, or another competing explanation.

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Evidence from herbal medicine pharmacovigilance databases and signal-document analyses shows that adverse event reports and statistical signals can support safety surveillance, but they require cautious interpretation because spontaneous-report data are affected by reporting limitations, heterogeneous documentation, and uncertain causal meaning [1, 2].

Herbal medicines and natural product preparations also differ from many conventional medicines because their

safety interpretation may depend on botanical authentication, plant part, extraction method, formulation context, product quality, contamination or adulteration concerns, co-administered medicines, and patient self-medication patterns. These features mean that herbal pharmacovigilance cannot be reduced to generic adverse event counting; it must integrate product identity, exposure context, clinical vulnerability, reporting quality, interaction plausibility, and governance safeguards before a signal can be interpreted as a possible safety concern [3].

Computational pharmacovigilance offers a way to structure this complexity. Methods such as coding support, data normalization, duplicate detection, disproportionality screening, natural language processing, interaction mapping, knowledge-graph integration, and multi-criteria prioritization can help organize large and heterogeneous safety evidence. However, these methods should be framed as support for surveillance reasoning rather than as mechanisms that independently establish causality, incidence, product-specific risk, or regulatory actionability.

The aim of this article is to develop an original computational pharmacovigilance framework for herbal and natural product medicines. The proposed framework distinguishes statistical signals, clinical suspicion, mechanistic plausibility, reporting bias, product uncertainty, interaction risk, causality assessment, and governance actionability. It is aligned with the broader pharmacovigilance view that artificial intelligence and computational tools can assist signal management, but only when embedded in validated, explainable, expert-reviewed workflows with clear decision boundaries [4].

Pharmacovigilance for natural product medicines

A core challenge in herbal and natural product pharmacovigilance is that surveillance capacity depends not only on the existence of reporting systems but also on the ability of regulators, manufacturers, marketing authorization holders, clinicians, and pharmacovigilance personnel to collect, process, interpret, and act on safety information. Assessments of herbal medicine safety-monitoring systems indicate that institutional responsibilities, reporting pathways, and system capacity are essential for meaningful surveillance, especially when product identity and exposure details may be incomplete [5].

Stakeholder perspectives further show that herbal pharmacovigilance requires practical reporting improvements, clearer communication, and best-practice procedures that can be applied across different healthcare and regulatory contexts. Such recommendations are important because patients may not disclose herbal product use, clinicians may not ask about it systematically, and reporters may provide descriptions that omit plant part, preparation, formulation, dose documentation, co-medications, or the chronology needed for causality assessment [6].

Classification and coding are particularly important for herbal and traditional medicine pharmacovigilance because product names, traditional formulations, common names, botanical names, and adverse event terms may be inconsistently recorded. A reporting system that captures an adverse event but loses herbal product identity, preparation context, or coding specificity may still contribute to signal detection, but it weakens product-level interpretation and increases the risk of misclassification [7].

Regulatory diversity adds another layer of interpretive uncertainty. Herbal products, botanical preparations, dietary supplements, and natural product medicines may be governed through different frameworks across jurisdictions, and those differences can influence product information, quality expectations, postmarketing responsibilities, and the interpretation of safety reports. For this reason, computational pharmacovigilance for natural product medicines should explicitly separate signal detection from regulatory interpretation and should communicate when product identity, formulation quality, or governance context is uncertain [8].

Signal detection and interaction mapping

Computational signal detection begins with the recognition that spontaneous-report data can reveal reporting patterns but cannot by themselves establish incidence, causality, or patient-specific risk. Disproportionality screening can support signal triage when appropriate data and assumptions are present, while detection-algorithm choice can influence which product-event combinations are highlighted for further review [9, 10]. In the proposed framework, disproportionality is therefore treated as a prioritization function that requires transparent methods, reporting-bias assessment, confounding review, and subsequent expert interpretation.

Natural product identity normalization is a prerequisite for meaningful signal detection. Product names in adverse event databases may appear as brand names, common names, botanical names, spelling variants, abbreviations, or incomplete free-text mentions. Computational approaches using fuzzy string matching and neural similarity methods can broaden the capture of natural product mentions in pharmacovigilance data, supporting a product-identity layer before product-event signals are interpreted [11].

Interaction mapping is equally important because herbal and natural product reports may involve co-administered conventional medicines, cancer therapies, cardiovascular

drugs, anticoagulants, hepatotoxic medicines, nephrotoxic medicines, or other products that complicate interpretation. Knowledge-graph approaches can organize pharmacokinetic natural product–drug interaction evidence and help connect products, constituents, enzymes, transporters, medicines, and possible mechanistic pathways for triage [12].

Computational workflows also depend on validated coding, supervised automation, and human review. Artificial intelligence has been evaluated for automatic coding of patient adverse drug reaction reports, but such automation requires validation before integration into pharmacovigilance practice [13]. Broader reviews of artificial intelligence in pharmacovigilance similarly show that computational tools may support detection, coding, screening, and workflow prioritization, but they require oversight and cannot replace clinical and regulatory interpretation [14]. Herb–anticancer drug interaction analyses using global spontaneous-report data further illustrate that interaction signals require co-medication context, pharmacological plausibility, and cautious interpretation rather than direct causal classification [15].

Table 1 summarises computational signal detection and interaction mapping functions relevant to pharmacovigilance for herbal and natural product medicines.

Table 1. Computational Signal Detection and Interaction Mapping for Herbal and Natural Product Medicines: Adverse Event Coding, Reporting-Quality Assessment, Disproportionality Screening, Text Mining, Interaction Mapping, Mechanistic Plausibility, Causality Boundaries, and Validation Needs

Computational function	Core pharmacovigilance question	Required input data	Potential signal output	Bias or confounding concern	Causality boundary	Validation requirement	Framework role
Product identity normalization	Is the reported herbal or natural product identifiable enough for analysis?	Botanical name, common name, brand name, formulation, plant part, preparation details, free-text product description	Normalized product entity or unresolved identity flag	Product-name variation, misidentification, missing formulation details	Identity normalization does not establish product-event causality	Manual review of uncertain matches and synonym dictionaries	Entry gate for interpretable signal detection
Adverse event coding	Is the reported event coded consistently?	Reporter narrative, adverse event term, seriousness, outcome, chronology	Standardized adverse event term	Coding ambiguity, vague narratives, translation differences	Coding standardizes the event but does not confirm an adverse reaction	Coding audit and expert adjudication where needed	Event standardization layer
Duplicate detection	Are multiple reports likely to describe the same case?	Reporter type, dates, patient descriptors, product, event, narrative similarity	Duplicate or possible-duplicate flag	Duplicate inflation or incomplete matching	Duplicate handling changes signal strength but not causal meaning	Human review of suspected duplicates	Data-cleaning layer
Missing-data review	Are essential interpretive fields absent?	Product identity, exposure timing, co-medications, comorbidities, event onset, outcome	Missingness profile	Selective missingness and incomplete self-reporting	Missing data reduces interpretability and prevents strong inference	Minimum data-quality criteria and reviewer documentation	Reporting-quality filter
Reporting-quality assessment	Is the case sufficiently interpretable for triage?	Chronology, seriousness, exposure details, dechallenge, rechallenge, alternative causes	Report interpretability category	Reporter knowledge, stimulated reporting, incomplete clinical detail	A high-quality report supports review but does not prove causality	Structured quality rubric and expert review	Case-level interpretability layer

Disproportionality screening where supported	Is a product-event pair reported more often than expected within a database?	Spontaneous-report counts, comparator groups, coding terms, denominator context within the database	Statistical safety signal for review	Underreporting, notoriety bias, stimulated reporting, confounding by indication	Disproportionality does not establish incidence or causality	Sensitivity analyses, transparent thresholds, expert interpretation	Statistical triage layer
Text mining or natural language processing where supported	Are relevant products, events, or interaction clues present in free text?	Narratives, clinical notes, case descriptions, product mentions, co-medication text	Extracted product-event or product-drug relation	NLP error, documentation bias, synonym ambiguity	Extracted associations require verification and interpretation	Annotated corpora, performance testing, manual error review	Evidence-expansion layer
Interaction mapping	Could a co-administered medicine or product modify risk interpretation?	Herbal product, natural product, conventional medicines, timing, pharmacokinetic or pharmacodynamic evidence	Candidate interaction signal	Polypharmacy, comorbidity, disease severity, confounding by treatment indication	Interaction mapping suggests plausibility but does not prove clinical interaction	Pharmacological and clinical expert review	Herb–drug interaction triage layer
Mechanistic plausibility review	Is there a plausible biological or pharmacological explanation?	Constituents, pathways, enzymes, transporters, target effects, toxicological evidence	Plausibility category for prioritization	Incomplete constituent data, uncertain exposure relevance	Plausibility supports prioritization but not definitive causality	Literature review, toxicology review, expert interpretation	Mechanism-informed interpretation layer
Signal prioritization	Which outputs should be reviewed first?	Seriousness, signal strength, product uncertainty, interaction plausibility, patient vulnerability, report quality	Prioritized safety concern for review	Overweighting serious outcomes or frequent products	Priority does not equal confirmed risk	Multidisciplinary review and documented decision criteria	Triage-to-governance layer

Adverse event interpretation

Adverse event interpretation for herbal and natural product medicines must begin by separating an adverse event from an adverse reaction. A reported adverse event is a temporally associated health occurrence after product exposure, whereas an adverse reaction implies a suspected causal relationship that requires clinical, pharmacological, temporal, and alternative-cause assessment. Analyses of herbal medicine product reports in national pharmacovigilance systems show the value of structured adverse event coding, seriousness assessment, and causality categories, while also reinforcing that spontaneous reports remain hypothesis-generating rather than incidence-estimating evidence [16]. Reporting and evaluation systems for herbal medicine can improve interpretability when they capture seriousness, reporter information, product details, and causality-related fields, but the quality of the conclusion remains dependent on the completeness and reliability of the underlying case information [17].

Organ-specific adverse event interpretation requires especially cautious reasoning. Hepatobiliary reports associated with herbal medicines in global spontaneous-report data can identify suspected product-event patterns, but such reports may be affected by incomplete exposure histories, uncertain product identity, co-medications, pre-existing disease, and variable clinical documentation [18]. Formula-specific analyses of liver injury reports can help prioritize safety questions for further review, but they should not be read as providing incidence rates or definitive causal classifications in the absence of denominator data and corroborating evidence [19].

Patient context, comorbidity, and polypharmacy are central to interpretation because herbal and natural product use often occurs alongside conventional medicines and chronic disease management. Analyses of pseudoaldosteronism reports associated with Kampo formula use show that patient factors and co-administered medicines may shape interpretation of suspected adverse events [20]. Related work on Kampo formula-induced pseudoaldosteronism also illustrates why exposure duration, clinical factors, and self-reported information should be treated as interpretive inputs rather than as standalone proof of causality [21].

Causality assessment should therefore function as a structured interpretive step after signal detection, not as a computational label automatically produced by a statistical signal. For liver injury, structured causality methods such as RUCAM emphasize chronology, dechallenge, rechallenge where available, competing causes, risk factors, and prior evidence; this logic is useful for clarifying the boundary between a reported event, a suspected adverse reaction, and a more strongly supported causal interpretation [22]. In the proposed framework, adverse event interpretation therefore combines temporal association, seriousness, product identity, exposure documentation, co-medication review, pharmacokinetic and pharmacodynamic plausibility, reporting quality, confounding assessment, and explicit uncertainty communication.

Risk governance requirements

Risk governance for herbal and natural product medicine pharmacovigilance must treat computational outputs as inputs to scientific interpretation rather than as final safety determinations. Pharmacovigilance has been described as a form of scientific discovery that depends on transdisciplinary reasoning, while automation in medicine safety requires explicit boundaries around what algorithmic systems can and cannot decide [23, 24]. This is particularly important for herbal and natural product medicines because uncertainty may arise not only from the adverse event report but also from product identity, formulation variability, contamination or adulteration concerns, exposure documentation, and co-administered medicines.

Governance of artificial intelligence and machine learning in pharmacovigilance requires auditability, transparency, model monitoring, accountability, and clear operational procedures for human review. These requirements are not secondary technical details; they determine whether computational pharmacovigilance can be trusted as part of a safety workflow, especially when models process incomplete reports, heterogeneous narratives, or product names with uncertain botanical meaning [25].

Operational experience with machine learning in medicine and vaccine safety also supports a human-in-the-loop approach in which computational tools assist case processing, triage, and workflow prioritization without replacing qualified safety review. For herbal and natural product pharmacovigilance, this means that signals should be escalated through documented criteria that include seriousness, reporting quality, product-identity confidence, interaction plausibility, patient vulnerability, and the feasibility of corroborating evidence [26].

Explainability is a further governance requirement when artificial intelligence outputs may influence pharmacovigilance interpretation. A model that flags a product-event pair, extracts a narrative relation, or prioritizes an interaction concern should provide interpretable reasons, data provenance, and uncertainty boundaries so that clinical pharmacologists, toxicologists, pharmacovigilance reviewers, and regulatory safety experts can evaluate its relevance [27]. **Table 2** maps adverse event interpretation and risk governance requirements for herbal and natural product medicine pharmacovigilance.

Table 2. Adverse Event Interpretation and Risk Governance Requirements for Herbal and Natural Product Medicines: Product Identity, Exposure Documentation, Reporting Quality, Causality Assessment, Patient Context, Interaction Risk, Risk Communication, Expert Review, and Decision Boundaries

Governance or interpretation domain	Core question	Evidence needed	Risk addressed	Uncertainty source	Governance action	Decision boundary	Failure risk
Product identity	Is the product sufficiently identifiable?	Botanical name, common name, plant part, preparation, formulation, manufacturer where available	Misattribution of adverse event to the wrong product	Ambiguous product names, incomplete labels, self-reporting gaps	Product-identity review and uncertainty flag	No product-specific interpretation when identity is unresolved	False attribution and misleading signal escalation

Exposure documentation	What exposure was reported?	Start date, stop date, exposure duration, dose documentation without dose advice, route, frequency, co-products	Misinterpretation of temporal relationship	Missing dates, recall error, unclear preparation	Exposure chronology review	Exposure documentation supports assessment but does not prove causality	Weak temporal inference
Reporting quality	Is the report interpretable?	Narrative completeness, seriousness, outcome, reporter type, dechallenge and rechallenge where available	Overinterpretation of incomplete reports	Missing clinical detail and incomplete follow-up	Structured reporting-quality assessment	Low-quality reports may support detection but not strong causal interpretation	Inflated confidence in weak evidence
Duplicate detection	Are reports independent?	Reporter, event date, product, patient descriptors, narrative similarity	Duplicate-driven signal inflation	Similar narratives, incomplete identifiers	Possible-duplicate review	Duplicate removal changes signal strength but not causality	Artificial signal amplification
Causality assessment	Is the product-event relationship assessable?	Temporality, dechallenge, rechallenge, alternative causes, prior evidence	Confusing adverse event with adverse reaction	Incomplete clinical data and competing explanations	Structured causality review	Causality assessment requires clinical judgement	Causal overstatement
Patient context	Could vulnerability affect interpretation?	Age, sex, comorbidity, organ function where reported, pregnancy status where reported, baseline disease	Unsafe generalization from individual reports	Missing patient characteristics	Vulnerability review	Framework cannot provide patient-specific medical advice	Misleading risk communication
Interaction risk	Could co-administered medicines explain or modify the event?	Medication list, product timing, pharmacokinetic and pharmacodynamic plausibility	Missed herb–drug interaction concern	Polypharmacy and confounding by indication	Interaction-risk review	Interaction mapping does not prove clinical interaction	Failure to prioritize plausible interaction signals
Product quality uncertainty	Could adulteration, contamination, or formulation variability matter?	Product-quality information, formulation details, contamination or adulteration suspicion	Wrong causal target	Unverified product composition	Product-quality uncertainty flag	Do not infer constituent-specific causality without evidence	Misclassification of safety concern
Risk communication	How should uncertainty be communicated?	Signal status, evidence strength, reporting limits, causality assessment outcome	Public or clinical misunderstanding	Ambiguous wording and causal overclaiming	Use cautious signal language	Communication supports awareness, not treatment advice	Panic, reassurance error, or misuse
Expert review	Is the signal clinically and pharmacologically credible?	Case data, signal output, mechanism,	Algorithm-only decision-making	Expert disagreement and evidence gaps	Multidisciplinary review	Expert review informs but does not automatically	Unsupported escalation or dismissal

		toxicology, clinical context				equal regulatory action	
Regulatory interpretation boundary	Is the signal actionable beyond surveillance?	Corroborating evidence, product quality data, seriousness, plausibility, recurrence	Premature regulatory conclusion	Evidence incompleteness	Documented governance review	No regulatory claim without appropriate authority review	Overreach beyond evidence
Feedback loop	What should be improved after review?	Reviewer decisions, coding errors, missing fields, validation needs	Repeated data-quality failures	Untracked workflow learning	Update coding, reporting templates, model rules, and review criteria	Feedback improves surveillance but does not eliminate adverse events	Persistent surveillance blind spots

Proposed pharmacovigilance framework

The proposed computational pharmacovigilance framework treats artificial intelligence and machine learning as assistive safety technologies within a broader interpretive and governance system. Its first principle is that computational pharmacovigilance should support safer signal detection, evidence organization, and triage, while avoiding autonomous causal judgement, patient-specific advice, or regulatory classification [28]. The framework is conceptual and is intended to organize pharmacovigilance reasoning rather than to claim implementation, empirical validation, clinical validation, deployment, or authority acceptance.

The first stage is product and exposure identity. This stage captures herbal or natural product identity, botanical authentication where available, plant part, preparation method, formulation context, product quality uncertainty, exposure documentation, co-administered medicines, and patient context. The second stage is adverse event data intake, which includes spontaneous reports, clinical narratives, adverse event coding, seriousness, temporal association, dechallenge and rechallenge information where available, missing-data review, duplicate detection, and reporting-quality assessment. Molecular and mechanistic knowledge can enrich postmarketing adverse event interpretation when used to connect signals with plausible biological pathways, pharmacokinetic mechanisms, pharmacodynamic mechanisms, and product-related uncertainty [29].

The third stage is computational signal detection and interaction mapping. This stage uses disproportionality screening where supported, text mining or natural language processing where supported, clustering of report patterns, product-name normalization, interaction mapping, and knowledge-graph integration. Natural language processing and machine learning methods can expand adverse event detection from clinical records and narratives, but these methods remain dependent on documentation quality, annotated data, validation, and contextual interpretation [30].

The fourth stage is interpretation filtering. Here, computational outputs are reviewed through reporting bias, confounding, product misidentification, adulteration or contamination concerns, pharmacokinetic plausibility, pharmacodynamic plausibility, temporal association, dechallenge and rechallenge where available, seriousness, causality assessment, and evidence strength. Electronic health record-based natural language processing may add richer patient context and confounding information than spontaneous reports alone, but it also introduces its own documentation bias, heterogeneity, and validation needs [31].

The fifth stage is risk prioritization, expert review, governance actionability, validation planning, and feedback. Adverse drug reaction mining across different data sources requires attention to source-specific limitations, stakeholder needs, data provenance, and interpretive transparency [32]. The final framework therefore includes model monitoring, audit trails, risk communication boundaries, regulatory interpretation boundaries, no-medical-advice safeguards, and feedback loops that update coding, data-quality rules, signal-prioritization logic, and validation plans. Artificial intelligence in pharmacovigilance creates opportunities for efficiency and signal organization, but its limitations require expert oversight, validation, and cautious governance [33].

Table 3 presents the proposed computational pharmacovigilance framework for herbal and natural product medicines.

Table 3. Proposed Computational Pharmacovigilance Framework for Herbal and Natural Product Medicines: Product Identity, Signal Detection, Interaction Mapping, Adverse Event Interpretation, Causality Uncertainty, Risk Prioritization, Expert Review, Governance Actionability, Feedback Loops, and Validation Boundaries

Framework stage	Core purpose	Required input	Computational or interpretive function	Potential output	Uncertainty or bias concern	Governance requirement	Validation boundary	Risk-management value
Product and exposure identity	Establish what product and exposure are being evaluated	Botanical name, common name, plant part, preparation, formulation, product quality information, exposure chronology, co-medications	Product normalization, identity review, exposure documentation	Identified, partially identified, or unresolved product-exposure profile	Misidentification, adulteration, contamination, incomplete exposure detail	Product-identity governance and uncertainty flagging	Identity confirmation is required before product-specific interpretation	Prevents premature attribution to uncertain products
Adverse event data intake	Convert heterogeneous reports into interpretable safety data	Spontaneous reports, narratives, seriousness, outcome, temporal information, dechallenge and rechallenge where available	Coding, duplicate detection, missing-data review, reporting-quality assessment	Structured case profile	Duplicate reports, missing fields, coding inconsistency	Reporting-quality governance and audit trail	Automated coding requires validation and review	Improves interpretability and triage readiness
Computational signal detection	Identify product-event patterns for review	Coded events, normalized products, report counts, comparator data where appropriate	Disproportionality screening, clustering, text mining, NLP	Candidate statistical or narrative signal	Underreporting, stimulated reporting, confounding, database artefacts	Transparent method documentation	Signal output requires expert interpretation and corroboration	Supports early prioritization without causal overclaiming
Interaction mapping	Identify possible herb–drug or product–product concerns	Co-administered medicines, natural product entities, mechanisms, enzymes, transporters, timing	Knowledge graph mapping, relation extraction, pharmacokinetic and pharmacodynamic plausibility review	Candidate interaction concern	Polypharmacy, indication bias, incomplete medication lists	Interaction-risk review	Mapped interaction does not prove clinical interaction	Highlights co-exposure concerns for further review
Interpretation filters	Evaluate whether the signal is clinically and pharmacologically plausible	Case chronology, seriousness, product identity, co-medications, comorbidities, mechanisms, alternatives	Temporal review, confounding assessment, causality assessment, plausibility grading	Interpreted safety concern with uncertainty statement	Alternative causes, incomplete clinical data, product-quality uncertainty	Multidisciplinary expert review	Causality assessment remains evidence-dependent	Separates adverse events from suspected adverse reactions
Risk prioritization	Decide which signals require attention first	Seriousness, report quality, plausibility, vulnerability, recurrence, product uncertainty	Multi-criteria triage	Review priority category	Overweighting frequency or severity without context	Documented triage criteria	Priority does not equal confirmed risk	Allocates review resources transparently

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Governance actionability	Determine whether and how the signal can inform safety action	Interpreted evidence, uncertainty statement, expert review, corroborating evidence needs	Governance review and communication planning	Surveillance action, communication need, validation plan, or no immediate escalation	Premature regulatory inference	Regulatory interpretation boundary and communication review	No authority-level conclusion without appropriate review	Aligns signal interpretation with responsible safety governance
Validation planning	Identify evidence needed to strengthen or refute concern	Signal profile, data gaps, product quality needs, clinical context, mechanistic evidence	Validation pathway mapping	Proposed evidence plan	Confirmation bias and feasibility constraints	Independent review of validation strategy	Validation is prospective and cannot be claimed until completed	Converts uncertainty into structured follow-up
Feedback loop	Improve future surveillance quality	Review outcomes, coding errors, missing-data patterns, model errors, reviewer feedback	Model monitoring, reporting-template updates, rule refinement	Updated workflow and improved data-quality rules	Model drift, untracked process changes	Auditability, transparency, and version control	Feedback improves process but does not eliminate risk	Creates a learning pharmacovigilance system

Figure 1 illustrates the proposed computational pharmacovigilance framework connecting product identity, signal detection, interaction mapping, adverse event interpretation, risk governance, expert review, and feedback loops for herbal and natural product medicines.

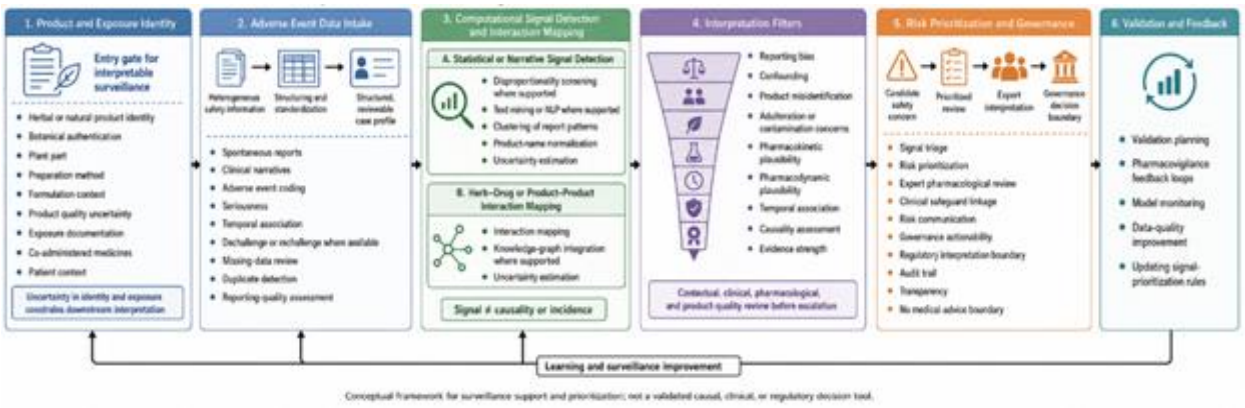

Figure 1. Computational Pharmacovigilance Framework for Herbal and Natural Product Medicines

Alt-text description

A conceptual pharmacovigilance framework showing herbal and natural product data flowing through product identity review, adverse event reporting, signal detection, interaction mapping, reporting-quality assessment, causality uncertainty, risk prioritization, expert review, risk governance, validation planning, and feedback loops.

CONCLUSION

This article proposed a computational pharmacovigilance framework for herbal and natural product medicines that integrates product identity, exposure documentation, adverse event data intake, signal detection, interaction mapping, adverse event interpretation, causality uncertainty, risk prioritization, expert review, governance actionability, validation planning, and pharmacovigilance feedback loops. The framework's central contribution is its separation of statistical signals from clinical suspicion, mechanistic plausibility, reporting bias, product uncertainty, interaction risk, and governance actionability. Computational pharmacovigilance can strengthen herbal and natural product medicine safety surveillance only when signals are interpreted through product identity, reporting quality, patient context, co-medication review, mechanistic plausibility, uncertainty communication, and governance safeguards. It should therefore be understood as a structured surveillance and prioritization approach, not as a substitute for clinical, toxicological, pharmacological, or regulatory review.

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