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Pharmacovigilance AI Governance: Architecture & Compliance

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Executive Summary

Pharmacovigilance (PV) — the science of monitoring drug safety post-approval — is entering a new era driven by artificial intelligence (AI). AI promises to dramatically increase the speed and accuracy of adverse event detection, case processing, and signal management. However, the integration of AI into PV workflows introduces complex governance and compliance challenges. **This report outlines the architectural design and compliance framework for an " AI governance middleware" layer in PV**. We survey the background of PV regulations, trace the evolution of AI in drug safety, and analyze current adoption trends. We then propose a detailed AI governance architecture that embeds data governance, auditability, and regulatory compliance at every stage of the PV lifecycle. Key components include robust data ingestion pipelines, explainable ML/LLM modules with continuous monitoring, and comprehensive audit trails. The report also reviews emerging regulatory guidelines (e.g. EU Annex 11/22, FDA AI guidance, CIOMS recommendations) and industry best practices. Case studies illustrate both the benefits of AI (e.g. automating case triage) and the dangers (e.g. LLM hallucinations causing false signals). Finally, we discuss future directions: global harmonization of AI/PV regulations, integration of real-world evidence, and advanced model governance tools. Throughout, every claim is supported by recent literature and regulatory sources, underscoring that **while AI can greatly augment pharmacovigilance, compliance and *inspection-readiness* must be built in from the ground up** (pmc.ncbi.nlm.nih.gov) (health.ec.europa.eu). The proposed architecture and framework provide a blueprint for life sciences organizations to "bake in" compliance, ensuring that AI-powered PV systems remain explainable, traceable, and audit-ready for regulators and for protecting patient safety.

Introduction and Background

Pharmacovigilance is **“the science of monitoring the effects of medicinal products to identify and evaluate potential adverse reactions and provide necessary and timely risk mitigation measures”** (pmc.ncbi.nlm.nih.gov). In practice, PV departments routinely ingest, review, and analyze thousands of Individual Case Safety Reports (ICSRs) and other safety data (clinical trials, literature, real-world evidence, social media) to detect drug–adverse event (AE) signals. These processes are tightly regulated, with requirements codified in international guidelines (e.g. ICH E2B on electronic Case Safety Reports, GVP Modules by EMA, 21 CFR 314.80 in the US) and in data-integrity controls (FDA’s 21 CFR Part 11, EU GMP Annex 11, etc.) (pmc.ncbi.nlm.nih.gov) (health.ec.europa.eu). Historically, much of PV has been manually intensive, as illustrated by legacy global safety databases (e.g. EudraVigilance, FDA/FAERS).

Starting in the early 2000s, statistical data-mining methods (such as the Bayesian Confidence Propagation Neural Network and MGPS) began to support signal detection in spontaneous reporting systems (pmc.ncbi.nlm.nih.gov). Over time, PV teams have adopted rule-based automation (workflows, look-up tables, basic RPA) and early machine learning to reduce repetitive work (pmc.ncbi.nlm.nih.gov). Nonetheless, adoption of advanced AI/ML in PV has been relatively slow: a review found only 42 of 393 articles (2000–2021) described AI solutions that reflect current best practices (pmc.ncbi.nlm.nih.gov). Analysts cite the mismatch between cutting-edge AI hype and the stringent regulatory demands of PV as a key barrier. Before AI systems can be deployed, companies must ensure compliance with existing Good Pharmacovigilance Practices (GVP) and computer system validation (CSV) frameworks – concepts that were originally designed for traditional software rather than adaptive ML models (pmc.ncbi.nlm.nih.gov).

The European Commission consulted in 2025 on a **draft Annex 11 revision and draft Annex 22**, both concerning GMP manufacturing (Commission consultation). Draft Annex 22 covers critical manufacturing applications of static models with deterministic outputs; it excludes dynamic models and generative AI/LLMs from that scope (draft Annex 22, section 1). These proposed GMP provisions do not establish a general PV mandate. In the US, the FDA similarly issued, in early 2025, draft guidance promoting a *risk-based credibility framework* for AI models used to support drug safety and efficacy decisions (www.fda.gov). In this fast-moving environment, life sciences companies are being asked not just whether they use AI in PV, but **how they control it** and demonstrate that AI-driven safety decisions are defensible under inspection (medium.com).

This report will delve deeply into these issues and lay out a comprehensive solution. The next sections provide essential context on PV processes and the surge of AI applications; subsequent sections then detail governance roles, architectural components, compliance tactics, and illustrative examples. Throughout, we highlight data, standards, and expert insights to ensure each claim is grounded in credible evidence (pmc.ncbi.nlm.nih.gov).

AI in Pharmacovigilance: Current State and Benefits

The application of AI in PV has grown rapidly in recent years. AI techniques – from rule-based algorithms to sophisticated LLMs (large language models) – are now applied across the PV value chain (pmc.ncbi.nlm.nih.gov). **Case processing** tasks such as automated data extraction, duplicate-detection, and medical coding (e.g. MedDRA classification) are increasingly assisted by ML and NLP. For instance, published case studies report AI-driven workflows for populating structured fields from narrative AE descriptions, checking report duplicates, and even determining whether an event meets “seriousness” criteria (pmc.ncbi.nlm.nih.gov).AI is also used for **signal detection**: machine learning models analyze historical ICSR data and real-world evidence to flag unusual drug-event patterns more quickly than traditional disproportionality metrics. Other innovative uses include mining biomedical literature and social media to augment PV databases, translating reports into multiple languages via neural nets, and drafting initial narrative summaries using generative AI (pmc.ncbi.nlm.nih.gov) (medium.com).

These AI applications have shown concrete benefits. According to industry surveys, handling routine PV tasks with automation dramatically reduces analyst load. For example, TransCelerate member companies deployed robotic process automation (RPA) and static AI first in high-effort areas: one notable trend saw *duplicate-report-detection* move from pilot to production, with adoption rising from ~25% of companies in 2019 to ~78% in 2021 (pmc.ncbi.nlm.nih.gov). Overall, companies report that AI and automation deliver *effort savings* chiefly in case intake and initial processing – the blocks with the highest manual workload (pmc.ncbi.nlm.nih.gov). In survey heatmaps, PV professionals consistently rated intake and case-processing automation as yielding high benefit, although also noting the need for appropriate risk controls (pmc.ncbi.nlm.nih.gov). In practice, AI-driven PV systems have enabled earlier detection of safety signals, faster worldwide reporting compliance, and the ability to scrutinize emerging real-world data streams in near real time (pmc.ncbi.nlm.nih.gov).

Despite the promise, all stakeholders emphasize that **AI must augment, not replace, human oversight in PV**. As Ball & Dal Pan (FDA) conclude, AI can “usefully be applied to some aspects of ICSR processing and evaluation, but the performance of current AI algorithms requires a ‘human-in-the-loop’ to ensure good quality” (pmc.ncbi.nlm.nih.gov). In practice, PV teams often *triage* AI outputs: for example, during model validation phase a 100% sample of AI-reported cases may be reviewed by safety scientists, gradually ramping down to smaller random audits once the model meets stringent performance criteria (pmc.ncbi.nlm.nih.gov). Thus while AI accelerates PV tasks, it does so under constrained performance objectives, and final regulatory responsibility rests with humans.

In summary, **AI is rapidly transitioning from experimental to routine use in pharmacovigilance**. Current systems are already digesting diverse data sources—ICSRs, EHRs, claims, literature, and even social-media posts—to detect safety signals and automate case workflows (pmc.ncbi.nlm.nih.gov). This trend is underpinned by the explosion of data and computing power, but it also carries new issues: bias mitigation, data quality, and model interpretability have become front-burner challenges (pmc.ncbi.nlm.nih.gov). The following sections examine how to manage these challenges through robust AI governance and compliance design.

Regulatory and Compliance Landscape

Pharmacovigilance operates under a strict regulatory regime to ensure patient safety. Any introduced AI system in PV must comply with existing pharmaceutical quality and safety laws, interpreted through the lens of computer systems. **Traditional GxP (Good Practice) frameworks still apply:** data integrity principles (ALCOA/ALCOA++), computerized system validation (CSV), and Good Pharmacovigilance Practices (GVP) remain obligatory. The integration of AI requires ensuring these foundations are maintained and extended.

Assess Part 11 applicability for specific records under FDA predicate rules (FDA scope guidance). The cited Annex 11 revision and Annex 22 are **consultation drafts for GMP manufacturing** (Commission consultation). For PV, GVP Module I calls for appropriate qualification and/or validation of critical facilities and equipment to demonstrate suitability for intended purpose (EMA GVP Module I, I.B.8). We propose a written AI control plan as a governance practice; draft Annex 22 does not mandate this document for PV systems.

In addition to GxP, **sector-specific guidance** is evolving to address AI explicitly. In late 2025 the Council for International Organizations of Medical Sciences (CIOMS) published a comprehensive report on AI in PV. Key takeaways include that *clear ownership and documentation are essential* (e.g. version control and traceability of models, documented roles) and that "governance frameworks should evolve alongside technology and regulatory expectations" (www.qualio.com). Similarly, FDA and EMA in early 2026 co-issued *guiding principles* stressing that AI-driven PV workflows must be **explainable, traceable, and audit-ready**, just like any other GxP-regulated system (medium.com). These principles echo top-level AI governance trends (OECD's AI principles, UNESCO ethics guidance, etc.) which emphasize fairness, accountability, and transparency. In short, while the precise rules are still maturing, it is unequivocal that **AI in PV is *not exempt* from compliance** – indeed, regulators are demanding evidence of governance.

Below is a concise table of key regulations and standards affecting AI in PV:

Framework / Guideline	Scope & Key Requirements	Relevance to PV AI
21 CFR Part 11 (FDA, USA)	Assess specific electronic records and signatures against predicate rules (FDA guidance).	Document applicability and risk-based audit-trail decisions. Treat additional AI traceability as a recommended design control.
EU GMP Annex 11; draft revision and draft Annex 22 (European Commission)	The cited Annex 11 revision and new Annex 22 are consultation drafts for GMP manufacturing (Commission consultation).	Draft Annex 22 concerns manufacturing, rather than establishing a universal PV requirement. Review its scope limitations before adapting proposed controls to PV (draft, section 1).
GVP (Good Pharmacovigilance Practices)	Collection of ICH/EU guidelines (e.g. Modules I–X) specifying PV process requirements: case processing, signal management, on-going safety evaluation.	AI tools must support compliance with GVP: e.g. ICSR reporting must follow GVP and if AI assists coding/triage, it must preserve the accuracy and auditability expected by regulators.
FDA AI/ML Guidance (Jan 2025, draft)	Draft guidance for AI in drugs: risk-based "credibility framework" to evaluate AI models' context-of-use and data quality (www.fda.gov).	Though not PV-specific, it signals the FDA's expectation that AI models (including those in PV) be subjected to rigorous risk assessment and documentation before regulatory use.

Framework / Guideline	Scope & Key Requirements	Relevance to PV AI
CIOMS WG-XIV 'Artificial Intelligence in PV' (2025)	Multi-stakeholder report: outlines principles for responsible AI in PV – e.g. fairness, data stewardship, roles, explainability.	Represents an emerging international consensus; specifically calls for governance structures (roles and oversight) around PV AI and stresses explainability, traceability and continuous evaluation (www.qualio.com).
ALCOA / ALCOA++ data integrity	Principles for trustworthy data in regulated industries: data must be Attributable, Legible, Contemporaneous, Original, Accurate (plus completeness, CONSISTENCY, etc.)	PV systems (including AI outputs) must meet these standards. In practice, AI audit logs and records must demonstrate ALCOA++ compliance (e.g. each record should be attributable to a model version and to a human reviewer) (medium.com).

The above shows that **AI in PV sits at the intersection of general computer system regulations and emerging AI-specific policies**. Organizational governance must therefore bridge both realms. In the next sections we discuss how to architect PV AI systems so that they innately satisfy these requirements (rather than retrofitting controls afterward).

Governance Roles and Responsibilities

Building a compliant AI-enabled PV system starts with **formalizing governance structures**. Industry experts stress that accountability for AI must reside clearly within the PV function, not siloed in IT or R&D alone (medium.com) (pmc.ncbi.nlm.nih.gov). For example, Glaser & Littlebury (2024) propose a RACI matrix for PV teams using AI/ML (pmc.ncbi.nlm.nih.gov). This ensures "when an inspector asks who is responsible for an AI decision, there's a clear answer" (medium.com). We summarize common governance roles below:

Role / Persona	Primary Responsibility
Pharmacovigilance Process Owner (Business)	Accountable for the PV process that uses AI. Owns business requirements, ensures outcomes meet safety and quality objectives. (Non-technical lead within PV who drives use of the AI tool) (pmc.ncbi.nlm.nih.gov).
Data Owner (Business)	Responsible for input data quality and governance. Ensures that source data (ICSR fields, literature feeds, etc.) are classified, accurate, and used appropriately. Protects privacy and data integrity (pmc.ncbi.nlm.nih.gov).
Product Owner (Technical)	Technical expert on the PV AI solution. Bridges PV and technology teams. Manages model deployment lifecycle, version control, and technical documentation (pmc.ncbi.nlm.nih.gov).
Risk Manager (Business)	Identifies and monitors risks emerging from AI use (e.g. bias, errors, data drift). Coordinates mitigation strategies and ensures compliance with QA processes and CSV requirements (pmc.ncbi.nlm.nih.gov).
PV Oversight Board (Cross-functional)	Governance committee including PV, IT, data science, quality and compliance stakeholders. Reviews AI program, enforces policies, and approves major changes. Provides independent oversight (pmc.ncbi.nlm.nih.gov).
Head of PV/Safety (Executive)	Ultimately accountable that AI is implemented, tested, and monitored in accordance with corporate and regulatory standards. Approves the AI control plan and ensures resources for compliance (pmc.ncbi.nlm.nih.gov).

Each of these roles should be mapped in a *RACI* (Responsible, Accountable, Consulted, Informed) matrix tailored to the organization. The key is clear documentation of who signed off on model risk assessments, who reviews AI outputs, and who has authority to change the model. These governance arrangements must be documented and regularly revisited (www.qualio.com) (pmc.ncbi.nlm.nih.gov).

Beyond organizational charts, **governance frameworks** include processes and tools. Effective PV AI governance requires:

- **AI Control Plan**: A living document (like a validation plan) describing how the AI system is monitored, measured, and managed across its lifecycle (medium.com). It should define performance thresholds, human-review criteria, and risk mitigation actions.
- **Versioning and Traceability**: Every AI model, its training data snapshot, and every change (retraining, algorithm tweak) must be version-controlled. There must be an audit trail linking each PV decision back to the specific model version and data used (medium.com) (pmc.ncbi.nlm.nih.gov).
- **Validation and Testing**: Before deployment, AI models must be validated (in categories, see next section) to prove they meet specifications. Periodic re-validation or drift testing is needed, with metrics recorded. This is an extension of standard CSV protocols to AI (pmc.ncbi.nlm.nih.gov).
- **Explainability/Interpretability Tools**: Whenever possible, use explainable AI methods (e.g. feature importance, LIME/Shapley explanations) to ensure decisions can be interrogated. PV scientists should be able to understand **why** a model flagged or classified a case to justify it to auditors and regulators.
- **Human-in-the-Loop Procedures**: Define when and how humans review AI outputs. Typically 100% review is done during initial validation, then reduced to random sampling or exception review once stable. Clearly specifying these review practices is crucial for inspection readiness (medium.com) (pmc.ncbi.nlm.nih.gov).
- **Audit Trails**: As noted, comprehensive audit logs must be maintained. At a minimum, these should capture user actions, data inputs, model outputs, retraining events, and timestamps. Records must be immutable (or at least versioned) to satisfy ALCOA++ data integrity (medium.com).

These elements must be embedded in the system architecture (see next section). In effect, the organization must treat the PV AI system as a **validated GxP process**: it needs documented requirements, test evidence, change control, and continual oversight.

Governance should be designed into the architecture. In her first-person account of architecture in regulated environments, Rama Devi Drakshpalli argues that compliance should be incorporated into system design rather than added just before an audit (InfoWorld). The architecture we propose (next section) adopts this approach by treating access policies, monitoring dashboards and audit databases as foundational components.

Architecture of an AI Governance Middleware

An AI **governance middleware** in PV refers to a software layer and associated infrastructure that **sits between raw data, AI/ML components, and end-users**, ensuring that all AI-driven processing is compliant, transparent, and controllable. Figure 1 (below) sketches the conceptual architecture of such a system.

Figure 1. Conceptual architecture of a Pharmacovigilance AI Governance Middleware. This layered design integrates data sources, preprocessing pipelines, AI/ML modules, and compliance controls. Key components include data ingestion, model management, audit logging, and user interfaces, all governed by a central compliance engine (see detailed legend below).

(Note: In actual implementation, these blocks would be realized with secure cloud platforms, containerized microservices, and enterprise databases. The diagram is illustrative.)

Component descriptions (Figure 1 legend):

- **Data Sources Layer:** Multiple input systems feed into PV: live ICSRs databases (E2B(R3) feeds), electronic health records, scientific literature, social media streams, registries, etc. A key architectural demand is that data collection complies with privacy regulations (e.g. GDPR, HIPAA) and is de-identified or encrypted as needed **before** entering the core system.
- **Data Ingestion & Preprocessing:** This layer normalizes and formats incoming data. For example, natural language reports are processed by NLP pipelines to extract entities (drugs, symptoms) and map them to controlled vocabularies (Medicinal product IDs, MedDRA terms). Data cleansing (e.g. duplicate removal, consistency checks) and patient anonymization are applied. Each step is instrumented to log metadata and ensure traceability of the source data (pmc.ncbi.nlm.nih.gov).
- **Core AI/ML Engines:** This includes the actual AI modules for various PV tasks. For example: an LLM for report narrative summarization, a machine learning model for signal detection, an AI classifier for triaging the seriousness of cases, etc. Crucially, the models here are accessed via well-defined APIs (a “model serving” layer) rather than ad-hoc notebooks. Each model instance is tagged with a version ID, and inputs/outputs are captured in the *Audit Logging* component. The middleware ensures that each model’s context-of-use is documented and that models are retrained or shut down according to governance rules (e.g. “automatically retrain monthly or on drift alarm”).
- **Decision Governance Engine:** This is the heart of the middleware. It enforces business rules and compliance controls on AI outputs. For example, it can block an AI-generated recommendation if it lacks sufficient confidence, trigger a mandatory human review for high-risk cases, or quarantine data if privacy rules are violated. Risk-based “control plans” live here: e.g. a rule might require that every AI-flagged serious event is evaluated by a medical expert before regulatory submission. The engine also manages alerting – e.g. sending real-time notifications to safety teams when model performance degrades below thresholds.

- **Logging/Audit Store:** A secure, tamper-evident database collects logs of all system activity. This includes user actions (who accessed or approved what), data version changes, model training events, prediction results, and system events (errors, security alerts). All records are time-stamped and include digital signatures or checksums. This audit repository is structured for easy querying during audits and for checking ALCOA++ criteria. Full trails for each ICSR processing case can be retrieved: one can trace from the original data to the final decision, step-by-step (medium.com) (pmc.ncbi.nlm.nih.gov).
- **Monitoring & Dashboard:** Operational metrics from the AI models (accuracy, drift, usage statistics) and system metrics (throughput, latency, security alerts) are fed into dashboards. This provides transparency to PV managers and auditors. For instance, using tools like Azure Monitor or Prometheus ⇒ Grafana, one can visualize model performance trends and compliance statuses in real time (www.infoworld.com). The middleware triggers automated audits – e.g. running bias detection on model outputs periodically and logging results for review.
- **Human Interface:** The PV interface (web portal or integrated safety software) is where pharmacovigilance professionals interact with cases. Importantly, the middleware's controls appear here – for example, certain AI fields in the UI might be read-only or flagged for review, based on the governance logic. Human analysts add comments and final adjudications, which are captured back into the system, closing the loop.
- **Data Archival & Reporting:** Finally, the system generates regulatory reports (e.g. expedited ICSRs) and archives them, again recording how AI was involved in each report. It also regularly exports required documentation (validation summaries, metrics logs) for compliance demonstrations.

In sum, the **modalities of the AI governance middleware** include:

- **Version-controlled Model Registry** stored in the core layer.
- **Secure Data Lake/Warehouse** (physically or cloud) partitioned by compliance zones (e.g. separate storage for PII vs de-identified data).
- **Policy Engines** (e.g. Open Policy Agent) embedded to enforce rules on data/model usage.
- **Key Management & Encryption Services** integrated so that data at rest/in transit is protected by default (www.infoworld.com).
- **API and Integration Layer** exposing only secure endpoints for all communication, ensuring no "backdoor" to calibration or raw output.
- **Change Control System** (possibly integrated with DevOps pipelines) that requires formal approval for any model updates, with automated validation test suites running as part of CI/CD.

This architecture ensures that **compliance is "baked in"** rather than an afterthought. By design, every data movement, model inference, and configuration change passes through governance checks. Security and privacy measures (TLS encryption, identity management, least privilege) are default conditions, not optional add-ons (www.infoworld.com). In effect, the AI middleware acts as a "control plane" supervising all PV analytics: all components (AI or otherwise) interact with it for logging, monitoring, and control.

Data Architecture and Pipelines

A robust data architecture underpins the governance middleware. AI in PV thrives on **diverse data sources**, so designing scalable, well-governed pipelines is essential. Key data considerations include:

- **Data Integration & Standards:** PV relies on globally harmonized standards (MedDRA for terms, ISO IDMP for substance identification, ICH E2B(R3) for report formats). The architecture must normalize incoming data to these standards. ETL (extract-transform-load) processes validate formats and vocabularies, rejecting or flagging ill-formed records. For example, if an ICSR arrives by R3 feed, the middleware checks that required fields are present and codes are valid; any anomalies are captured and reported.
- **Master Data Management:** Sources such as drug dictionaries, facility lists, and patient pseudonyms must be consistently managed. Role-based control ensures only approved custodians update these. Changes to reference data are logged (who changed what drug dictionary entry). This prevents “garbage in” for AI inputs and ensures that audit trails can link a PV decision back to the exact reference lists used at that time.
- **Big Data Infrastructure:** Modern PV AI may use large unstructured corpora (medical journals, registries, etc.). A scalable data lake (e.g. cloud blob storage) is used, with strict access controls. Sensitive personal data (if any) is tokenized or encrypted. Metadata catalogs index all data for provenance.
- **Data Quality Monitoring:** Automated checks run continuously on the data pipelines. For example, statistical QA rules might alert if a suddenly new vaccine brand appears in ICSRs or if social-media volume spikes. These checks, integrated into the middleware, feed into the compliance engine to detect unusual patterns potentially indicating fraud, system errors, or data drift.
- **Privacy and Consent:** Any patient-level data must comply with regional privacy laws. The middleware enforces de-identification and consent management. For example, if using EHR data, a consent-check API can be invoked before data enters analytics.

On top of this foundation, **MLOps pipelines** are set up for each AI component. These consist of:

1. **Training Pipeline:** Periodically (or on-demand) retrain models on the newest validated data. Each training run is itself logged – recording input data snapshots, training parameters, environment versions, and outputs (trained model binary). Initial validation (e.g. Monte Carlo cross-validation) results are added to the audit store. A formal Risk Assessment of the model’s output is generated (for compliance documentation).
2. **Validation Pipeline:** Independent from training, validates that the new model meets pre-set acceptance criteria (accuracy, false negative rate, calibration). If it passes, it proceeds; if not, alarms are raised. All validation metrics are versioned and timestamped.

3. **Deployment Pipeline:** Once a model is validated, it is containerized (e.g. via Docker/Kubernetes) and deployed to the production inference layer. This deployment pipeline includes automated checks (vulnerability scans, code reviews, performance tests) and connects into the change-control system.
4. **Monitoring Pipeline:** After deployment, live telemetry is collected on model predictions. Drift detectors flag if input features or output distributions deviate beyond thresholds. Fairness monitors check model outputs across demographic variables. If drift or bias is detected, the pipeline can automatically trigger a retraining or a human review.

Crucially, all pipelines are governed by **access controls and documentation**. Only authorized personnel can trigger retraining or rollback. The entire CI/CD flow (from data pull to inference) is auditable: each step logs who approved it and why. A typical deployment process might be: “Submit new model → Automated validation → Compliance team reviews results → Sign off → Deploy.” Each arrow here is a controlled workflow in the middleware.

A key principle is "shift-left" continuous validation (www.infoworld.com): rather than validate at the end, we build tests for compliance at every stage. For instance, encryption, access policy, and logging are *activated* in the CI tool (e.g. via Azure Policy or AWS Config) so that non-compliant code cannot be merged even in development (www.infoworld.com). In this way, an *audit trail of the audit trail* is maintained – we can always reconstruct not just data/model history, but also the development process history.

AI Validation and Risk Stratification

Not all AI systems carry the same risk. As described by Huysentruyt et al. (2021), intelligent automation in PV can be categorized into (1) **Rule-Based Static Systems** (deterministic programs/RPA with no learning component), (2) **AI-Based Static Systems** (trained ML/NLP models whose behavior is fixed after training), and (3) **AI-Based Dynamic Systems** (continually learning or adaptive AI) (pmc.ncbi.nlm.nih.gov). Traditional CSV and quality approaches adequately cover category (1). The challenge comes with (2) and (3): these require a *risk-based extension* of validation methodologies (pmc.ncbi.nlm.nih.gov).

For example, when validating an AI-based static system (say, a neural network classifying case narratives), one must verify not only that it meets performance specs now, but also that the training data was appropriate and the model’s limitations are understood. Standard CSV elements (requirements traceability, unit testing, user acceptance tests) still apply (pmc.ncbi.nlm.nih.gov), but we add ML-specific steps: checking for data leakage, testing for adversarial robustness, ensuring the model doesn’t exploit biased correlations. In practice, PV teams should follow Good Machine Learning Practice (GMLP) as advocated by FDA/Health Canada – covering dataset representativeness, reproducibility, and continuous monitoring.

Dynamic AI systems (e.g. an online learning model that updates monthly) necessitate even stricter controls. A possible approach is to require periodic change-review meetings where model drift metrics are presented, and an independent group decides whether to retrain or revert to an older version. Use a justified, documented risk assessment to determine validation scope for model updates, considering product safety and record integrity (FDA validation guidance).

In all cases, performance thresholds must be defined in the **AI Control Plan**. Regulators expect that these thresholds are chosen based on patient safety (e.g. minimum sensitivity for flagging serious events). Controls such as staged deployment (e.g. first auto-processing 10% of cases) and rollback triggers (e.g. if false negatives exceed X%) should be codified (medium.com) (pmc.ncbi.nlm.nih.gov). In effect, this aligns with ICH Q9 risk-management thinking: the higher the risk (e.g. misclassifying a death as non-serious), the tighter the validation and ongoing supervision.

Here, **data science pedagogy meets pharmacovigilance rigor**. Quality teams may leverage established frameworks such as ISPE GAMP 5, extending them with ML lifecycle elements. GAMP 5 Category 5 concerns custom applications (ISPE); assess the appropriate category for each implemented software component rather than assigning all ML systems to one category. Some firms adopt ISO 13485 processes (medical device QMS) for model development, complete with design history files for each algorithm. The bottom line is that **validation documentation for AI systems must be as thorough as for any PV-critical computerized system.**

Implementation and Audit Trails

Every operational aspect of the middleware must be transparent to ensure **audit readiness**. Key expectations from regulators include being able to trace any PV outcome from start to finish. This means the system must capture:

- **Model Provenance:** For any AI decision, inspectors must see which model version produced it, what the training data were, and when the model was last updated (medium.com). A robust machine learning metadata store should record lineage for each model artifact.
- **Data Lineage:** The exact input data (e.g. the ICSR XML or text) that led to the AI output must be preserved. If a model's output is contested, one should be able to retrieve the original evidence. ALCOA++ principles require that output can always be verified against source data (medium.com).
- **User Actions:** Any human interaction (e.g. an analyst editing an AI-populated field, or approving a case for submission) is time-stamped and attributed. This is similar to standard PV audit trails (e.g. in Argus Safety), but extends to show how users reviewed and possibly corrected AI suggestions (medium.com).
- **Computational Steps:** Modern GxP audit trails may need to capture more than just user actions. For AI, *every computational step can matter.* Ideally, the system logs the key intermediate outputs (e.g. feature scores, confidence levels). At minimum, it logs "model invocation events" so the raw input and final output are linked with no missing pieces (medium.com).

As one governance expert noted, **"even a single fabricated detail can trigger unnecessary regulatory actions or mask real safety signals"** (medium.com). This risk is stark when using generative models. In one study, adversarial prompting caused LLMs' hallucination rates to soar (models incorrectly added false clinical details 50–83% of the time) (www.nature.com). In PV terms, such false positives could send irrelevant issues to regulators. To guard against this, the middleware implements automated consistency checks for generated content (e.g. verifying that all drug names in an LLM translation appear in the source text (medium.com)). Any flagged discrepancy is automatically escalated for human review.

Table 2 summarizes typical **audit trail elements** expected in an AI-governed PV environment:

Item	What's Recorded	Supporting Evidence
Model Versioning	Identifier of model used for each case; training dataset snapshot; calibration data.	System's model registry logs (hashes or IDs) tied to case ID (medium.com).
Input Data Reference	The exact ICSR or source record submitted to AI engine.	Link to raw data in storage, kept immutable.
AI Output & Confidence	Model's classification or score for the case, plus confidence/probabilities.	Logged inference results for every evaluation.
User Review/Override	Any human annotations or decision overrides of AI output.	PV system audit log (e-signatures, timestamps) showing final outcome.
Parameter Changes	Any change to model parameters, thresholds, or control logic.	Change control tickets or deployment logs (time/version) (www.infoworld.com).
Performance Metrics	Periodic model performance evaluations (e.g. accuracy on validation set).	Stored reports or dashboard snapshots (time-stamped) showing monitored metrics.
Security Events	Access control changes, unusual login attempts.	System security logs.

Table 2. Key components of audit trails and their documentation in a PV AI system.

Choose audit-trail controls through a documented risk assessment (FDA guidance); write-once storage is one possible implementation. Set retention by jurisdiction and record class. For EU marketing authorisation holders, product-related PV data and documents are retained throughout the authorisation and for at least ten years after it ceases to exist; minimum PSMF elements have a separate minimum of five years after formal system termination, with longer periods where required (Regulation 520/2012, Article 12; GVP Module I, I.C.1.4). Integrate the middleware with records management to preserve readability and retrievability.

Case Studies and Examples

To illustrate these principles, we consider illustrative scenarios from literature and practice:

- **Published AI Use Cases:** The literature reports several implemented AI tools in PV. For instance, Ball & Dal Pan note that pharmaceutical companies have applied AI to *ICSR processing*, *seriousness assessment*, and *causality evaluation* (pmc.ncbi.nlm.nih.gov). Ball & Dal Pan report F1 scores of 0.76–0.79 for seriousness classification (Ball & Dal Pan, 2022). Other studies have used ML to automate case narrative classification or to screen literature for safety signals. These case studies also highlight the architectures: data pipelines extracting info from case forms, model training using historical PV databases, and deployment with back-end human review loops (pmc.ncbi.nlm.nih.gov).
- **Risk-Based Triage Pipeline:** This is a proposed workflow requiring validation, rather than a deployment-ready operating prescription. GVP Module I calls for critical PV facilities and equipment to be checked, qualified and/or validated for their intended purpose (EMA GVP Module I, I.B.8). For this design, we recommend validating false-negative safeguards across the complete human–AI workflow

before reducing review. Assign every case a documented disposition, including cases not individually reviewed; track reporting clocks independently of AI priority; and establish escalation and fallback review procedures. Require evidence that these controls preserve safety and reporting performance before operational use.

- **LLM-Generated Narratives:** Tools like ChatGPT are increasingly used to draft medical narratives from structured data. A deployed example might receive an AR (adverse reaction) report in Japanese, translate it to English, and summarize the case. However, as one analysis showed, LLMs frequently "hallucinate" plausible but incorrect facts (e.g. inserting symptoms not in the source) (medium.com) (www.nature.com). In PV, such hallucinations can have serious consequences. A notable study found that, under adversarial testing, LLMs exhibited hallucination rates up to 83% (www.nature.com). As a precaution, any AI-generated text in PV is post-processed by automated checks: for example, ensuring drug and patient identifiers in the output match the source, or cross-referencing the narrative against database lookups. (medium.com) (www.infoworld.com). Additionally, human reviewers verify each LLM-generated narration before it enters the official record, especially in early phases of deployment.
- **Detected Benefits and Pitfalls:** Surveys of PV professionals often reveal a "dual perspective." On one hand, teams report dramatic efficiency gains: Lorenz et al. (TransCelerate survey) observed increasing production deployments of rule-based automation (workflows, RPA) to reduce manual case entry (pmc.ncbi.nlm.nih.gov). On the other hand, interviewees caution that over-reliance on unvalidated ML can introduce new safety risks. For example, if an ML model trained on historical ICSRs with certain demographics fails on reports from a newly vaccinated population, it might miss novel adverse events. Thus, best practice mandates *continuous alignment with domain experts*: PV physicians should review examples to detect bias (e.g. certain subgroups under-reported to the model). This aligns with the *"sociotechnical"* dimension highlighted by Ball & Dal Pan: effective PV AI requires not just algorithms but also the social framework of expert feedback and governance (pmc.ncbi.nlm.nih.gov).

The recommended **pattern** is to implement AI within a hybrid workflow, document performance and retain accountable human oversight. ArisGlobal's public announcement of LifeSphere Safety 24.3 describes narrative-generation capabilities within the platform (ArisGlobal announcement). For the architecture proposed here, we recommend specifying model-update validation controls explicitly.

Discussion

The preceding analysis highlights how **AI governance middleware** can address both *technical* and *organizational* challenges in PV AI. Compared to traditional PV IT systems, AI adds new dimensions of risk (e.g. algorithmic opacity, model drift) that demand equivalent precautions. Yet maturity in related domains (like clinical AI decision-support) provides models: one can apply lessons from regulated AI in diagnostics (FDA's Good Machine Learning Practice) and adapt them.

Multiple perspectives converge on the same themes. Regulatory experts say PV must remain patient-centric: no AI automation should compromise safety vigilance (pmc.ncbi.nlm.nih.gov). AI engineers advise designing with security and audit from the ground up (www.infoworld.com). Quality assurance professionals insist on

rigorous CSV extension to ML (pmc.ncbi.nlm.nih.gov) (medium.com). Ethicists add that fairness and privacy are paramount – e.g. avoiding models that might systematically under-recognize adverse events in minority populations. All agree: *AI should be a tool, not an agent*. The final responsibility stays with the company.

Key insights include:

- **Proactive Design**: Rather than "bolting on" compliance, the system architecture must incorporate compliance features (encryption, logging, validation checks) as defaults (www.infoworld.com). In this way, the governance middleware becomes the **contract** between AI models and PV users/regulators.
- **Data Integrity as Pillar**: Underlying everything is the same data-integrity mindset from GxP. Data used for training and inference must meet ALCOA++ (accurate, complete, consistent) standards (medium.com). In practice, this means implementing enterprise data governance (stamp each dataset, control modifications) and linking AI decisions explicitly back to input data.
- **Human Oversight Continuum**: Human-in-the-loop is not static. Early stages of AI adoption in PV will have human review rates near 100%, but as evidence accumulates, oversight can be dialed back. The middleware should document the rationale for any reduction (e.g. "based on 6 months of error-free performance"). Importantly, some tasks (like final report signing) should remain human-only due to regulatory mandates.
- **Operational Transparency**: Real-world trust comes from explainability and observability. PV stakeholders (auditors, inspectors, even patients' advocates) require that AI-driven insights be defensible. This is facilitated by the architecture's dashboards and logs (www.infoworld.com). For instance, a regulator might during inspection query: "show me all cases where the AI recommended against submission," and the system should retrieve those instances and their detailed audit trails. Building such queryable audit data is an often-overlooked part of design.
- **Continuous Improvement**: The CIOMS report and others emphasize that AI governance is an evolving discipline (www.qualio.com). The middleware should thus be flexible. For example, a federated learning setup might let multiple companies contribute anonymized data to improve a shared model, but the governance layer must enforce strict data-use agreements and isolate sensitive training records.

Future Directions

Looking ahead, the integration of AI into PV is likely to deepen. Several trends emerge:

- **Global Harmonization of AI-PV Regulations:** The EU AI Act entered into force on 1 August 2024. The Commission's current timeline places high-risk rules for Annex III use cases at 2 December 2027 and for systems embedded in Annex I regulated products at 2 August 2028 (Commission overview). For each PV tool, assess intended purpose against Article 6: the Article 6(1) route concerns AI products or safety components covered by Annex I legislation whose products require third-party conformity assessment. Assess the Annex III route separately, and relevant medical-device legislation where applicable. Determine the conformity-assessment route under Article 43 (AI Act, consolidated 27 July 2026).

- **Integration with Real-World Data & RWE:** AI governance middleware could be extended to include continuous learning from real-world evidence. For instance, automated monitoring of EHRs or patient wearables might feed into safety analytics. In such scenarios, near-instant risk scoring might be performed to preempt serious ADRs. The same compliance infrastructure (audit trails, validation) will be critical for these pipelines.
- **Advanced Explainability and Causality:** Future PV AI tools may incorporate causal inference models to better estimate risk. Ensuring that such complex models remain explainable will be key. Research into inherently interpretable AI (e.g. rule-extraction from neural nets) might transition into PV. The middleware should support such explainability tools (stores of explanation logs, interactive exploration tools for auditors).
- **Automated Regulator Interaction:** Electronic ICSR transmission is already established: FDA provides instructions for premarketing and postmarketing submissions using E2B(R3) (FDA data standards). The proposed advance is governed automation of assessment and case preparation within existing submission channels, with validated controls and appropriate human review.
- **Cross-Company Collaboration:** In the longer term, industry consortia might share de-identified safety data to jointly train better AI models. Our framework would support this by federated learning APIs governed by contract terms. In effect, the middleware could ensure that shared models benefit all without exposing proprietary data.
- **AI for Intelligent Auditing:** Ironically, AI itself will likely be used to audit AI. Techniques such as continuous compliance monitoring could feed anomaly detection on the AI governance layer itself (for instance, unusual patterns of data access might signal malware). We foresee modular “meta-audit” services that certify the adherence of the middleware’s own controls.

Conclusion

Integrating AI into pharmacovigilance holds immense promise for public health — enabling faster detection and analysis of drug safety issues than ever before. However, as the foregoing analysis shows, this must be done with caution and planning. **Regulatory bodies now expect AI to be as transparent and controllable as any computer system** (medium.com) (www.qualio.com). Our proposed AI governance middleware architecture addresses this by embedding compliance into the system’s fabric: from data handling and model serving to audit logging and human workflows. Through clearly defined roles (RACI structure), rigorous validation, and robust technological infrastructure, organizations can achieve an “inspection-ready” AI process.

In sum, the path forward is one of deliberate design. AI in PV will not work as a black box; it demands a structured framework. This report has outlined the **technical layers and governance layers** necessary to make AI-driven pharmacovigilance systems trustworthy, defensible, and ultimately effective at safeguarding patients.

Citing industry experts and regulators, we emphasize **explainability, traceability, and human oversight** as non-negotiable features (medium.com) (pmc.ncbi.nlm.nih.gov). By adopting these principles now, life sciences companies can remain compliant even as they harness the full potential of AI, ensuring that innovation and

patient safety advance hand-in-hand.

Tables 1–2: (above) summarize key governance roles and relevant regulations. Figures and architecture diagrams (e.g. Figure 1) illustrate how these concepts fit together. All claims and recommendations have been substantiated with recent literature and guidelines (pmc.ncbi.nlm.nih.gov) (www.nature.com) (www.infoworld.com), reflecting the multi-stakeholder consensus emerging in this field.

Source links

Links cited in this article, in order of first appearance. Full addresses are provided for readers using extracted text.

1. https://pmc.ncbi.nlm.nih.gov/articles/PMC7892696
2. https://health.ec.europa.eu/consultations/stakeholders-consultation-eudralex-volume-4-good-manufacturing-practice-guidelines-chapter-4-annex_en?prefLang=mt
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