Application of Artificial Intelligence in Pharmaceutical Manufacturing

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The presenter used AI tools for image generation

Outline

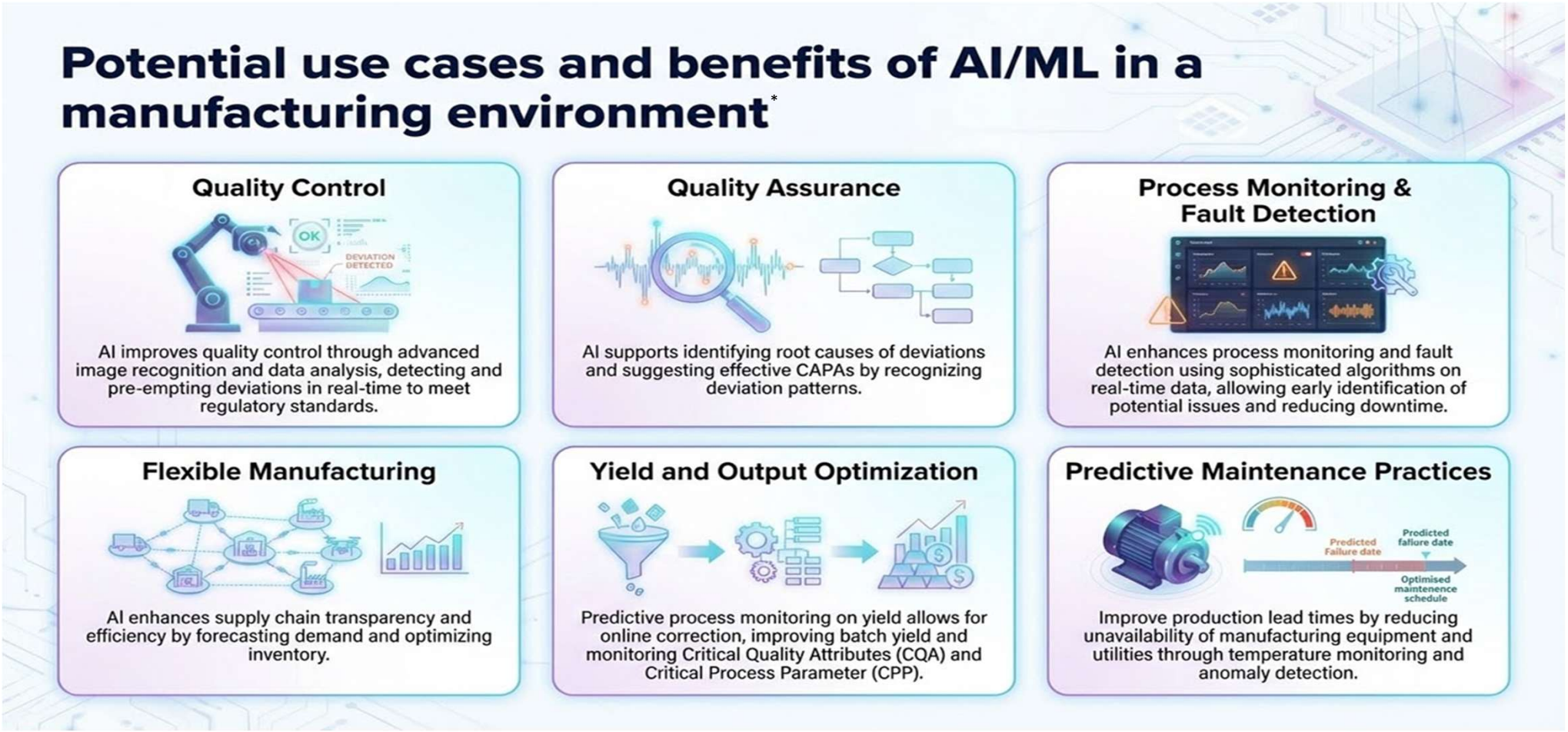
- Introduction
- AI in pharma manufacturing – examples
- Emerging regulatory guidelines
- Concluding remarks

Introduction – AI/ML in pharmaceutical manufacturing

AI and ML in Medical Products Lifecycle

- Artificial Intelligence (AI) and Machine Learning (ML) are transforming the pharmaceutical landscape, offering unprecedented opportunities throughout the entire drug development life cycle, including accelerating drug discovery, optimizing clinical trials, enhancing manufacturing precision, and post-approval safety monitoring

AI optimizes production by monitoring processes in real-time and detecting anomalies through tools such as computer vision in packaging, ultimately improving yield and consistency. Additionally, it facilitates predictive maintenance to help prevent equipment failures



* 2024 EFPIA position paper application of AI in GMP manufacturing

AI in pharmaceutical manufacturing

- **Process Design and Scale-up**: ML models use development data to identify optimal parameters, reducing development time and waste.
- **Advanced Process Control (APC):** AI integrates real-time sensor data with chemical and biological modeling to enable dynamic control and predictive process progression.
- **Monitoring and Fault Detection:** AI detects equipment deviations for proactive maintenance and uses vision-based systems to automate quality control for packaging and labeling.
- **Trend Monitoring:** AI analyzes text from complaints and reports to identify improvement clusters, supporting root cause identification and predicting thresholds for corrective actions.

AI and ML in pharma manufacturing – application examples

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AI for clustering of information in continuous improvement

Machine Learning Models for mAb process predictions

Deep learning algorithms to improve automated visual inspection

GenAI Natural Language Processing (NLP) based clustering of deviations for continuous improvement

An AI tool for deviation clustering and analysis

Problem statement:

- In large manufacturing networks, there is a wealth of information to be data-mined for continuous improvement
- Manual study of free text fields is very labor intensive

What is NLP-based clustering and How Can It Improve Manual Processing?

- For deviations, one can use textual data (like titles and descriptions) to extract key topics and cluster similar deviations. => known as topic modeling, is a part of NLP.
- Helps with ***targeting continuous improvement efforts*** across a large manufacturing network

Part of a larger set of applications around GenAI generating or analyzing text

- Many applications of «AI» in Pharma manufacturing and technical development use **Large Language Models** for text
  - Regulatory: Content generation for dossier, Q&A analysis
  - Quality: Improvement of reporting through suggested categorization
  - Technical development: Report generation, advanced search and knowledge mgmt

Machine-learning models to predict mAb batch yield

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An AI tool for improving planning and scheduling

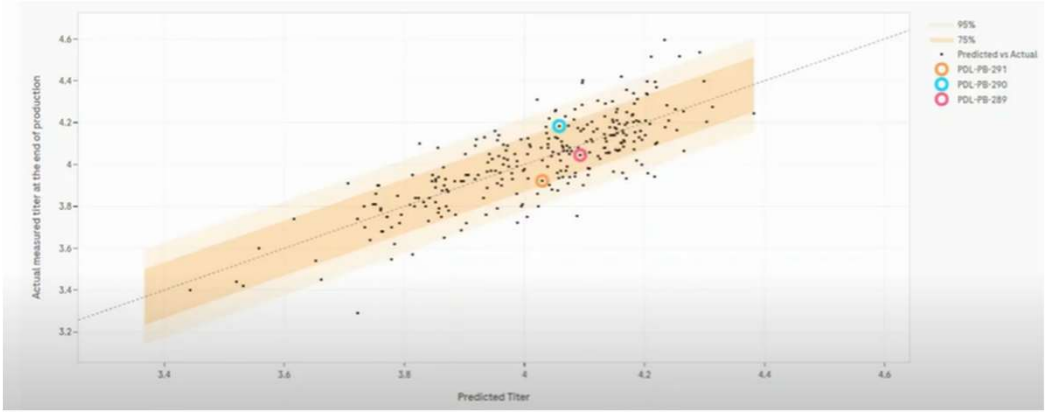
Problem statement:

- In large scale mAb DS production, there is an inherent variability in the process, resulting in variability of processing times etc.
- The experiences gained with a product made over the lifetime of manufacturing is not easily translatable into actionable knowledge

Digital model of a manufacturing process

Could be of entire process or individual steps

- Here: prediction of titer/yield for mAb DS process



ML Deep Learning Models to improve automated visual inspection

ML algorithms improve quality assurance of parenteral product inspection

Problem statement:

- 100% in-process inspection of parenteral products – followed by a lab-based AQL test of a subset of samples - is a regulatory requirement
- Manual (human operator) based visual inspection is well established, but can be a bottleneck
- Automated visual inspection (AVI) with conventional algorithms can produce a significant amount of false positives

Advances in deep learning offer reduced classification error rates.

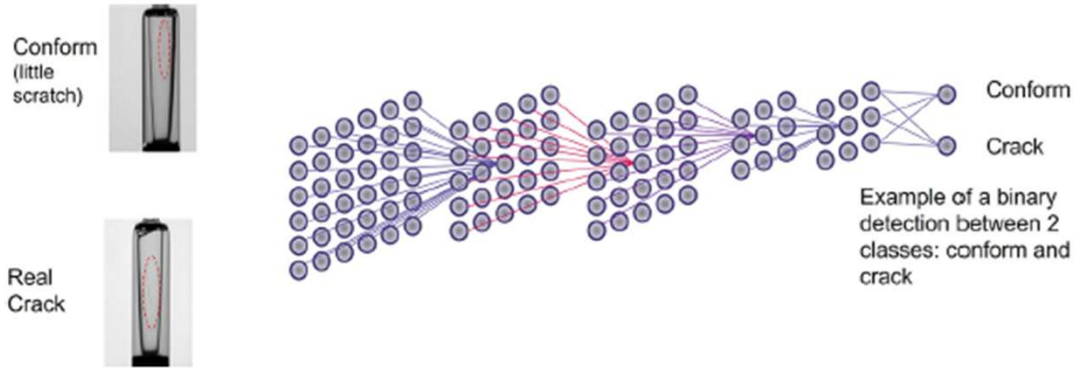


Image source: PDA Journal of Pharmaceutical Science and Technology, Vol. 77, No. 5, September--October 2023

Visual Inspection Algorithms powered by Deep Learning

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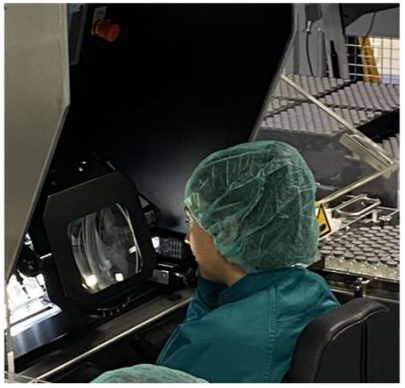
Reality today, potential for autonomous learning tomorrow

Camera-based Visual Inspection, powered by Deep Learning/neural network algorithms for image processing

From here...



...to here

Challenge with conventional image detection algorithms:: High false reject rate

- Requiring manual re-inspection
- Delayed product release
- Potential loss of good product

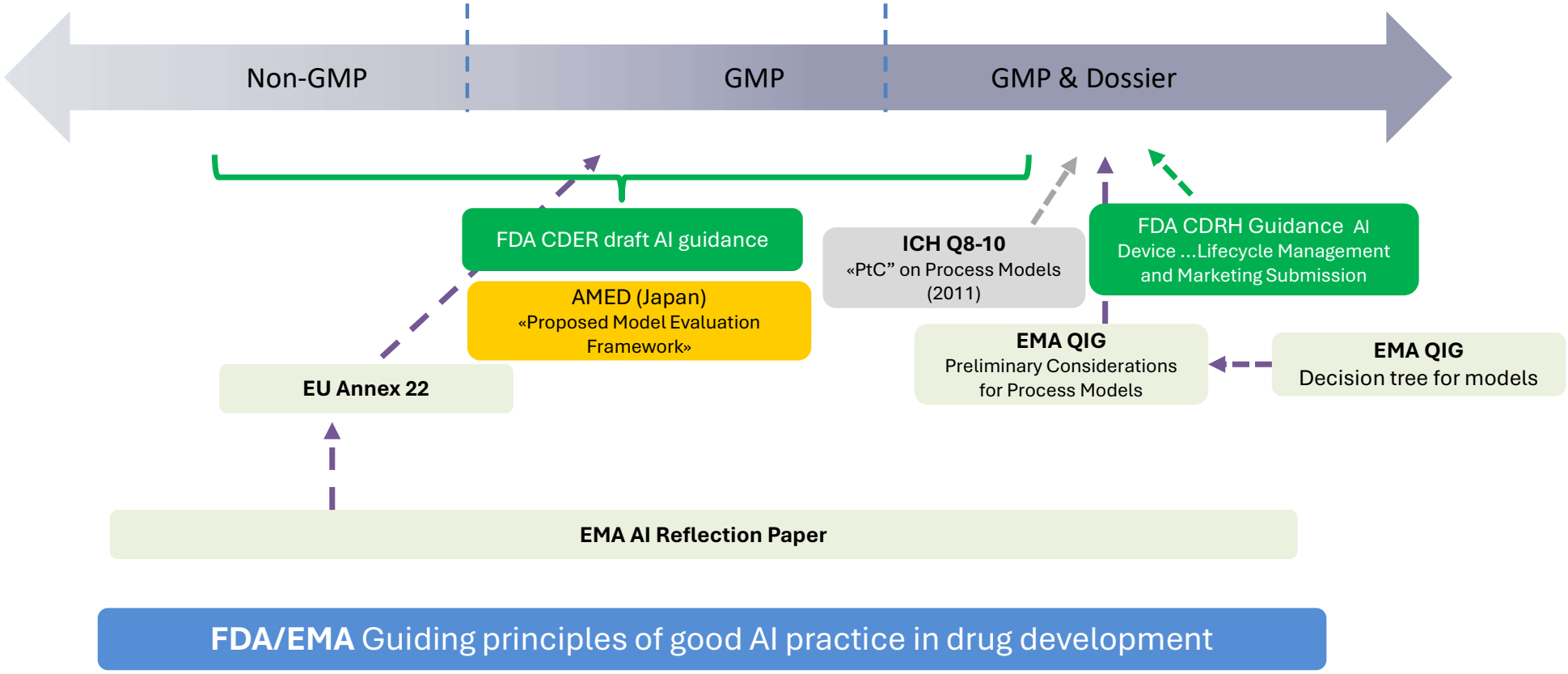
Machine learning algorithms technology improves the detectability of true defects while minimizing false rejects.

Use of AI for visual inspection – challenges

- **Data Scarcity & Quality:** Pharmaceutical manufacturing aims for near-zero defect rates. This makes it difficult to assemble large, diverse, balanced datasets of labelled defect images (e.g., glass particles, plastic fragments, bubbles, cracks, or artifacts like reflections)
- **False positives/negatives and performance variability**: AI may misclassify borderline cases (e.g., distinguishing cracks from optical artifacts or bubbles from contaminants. While AI can reduce false reject rates (FRR), it requires precise tuning to manage false positives and negatives.
- **Environmental Sensitivity:** Small changes in lighting, camera angles, or reflections on glass/plastic can lead to significant drops in model accuracy (data drift)
- **"Human-in-the-Loop"** philosophy: To maintain compliance with Annex 1 requirements, AI should complement rather than replace human oversight. Product release testing (QC testing) ensures products meet the expected standards
- **Continuous Learning & Feedback:** When the AI is uncertain the image is routed to a human expert. The expert's decision is then used as new training data to refine the model. Reviewing AI "decision logs" to ensure consistency

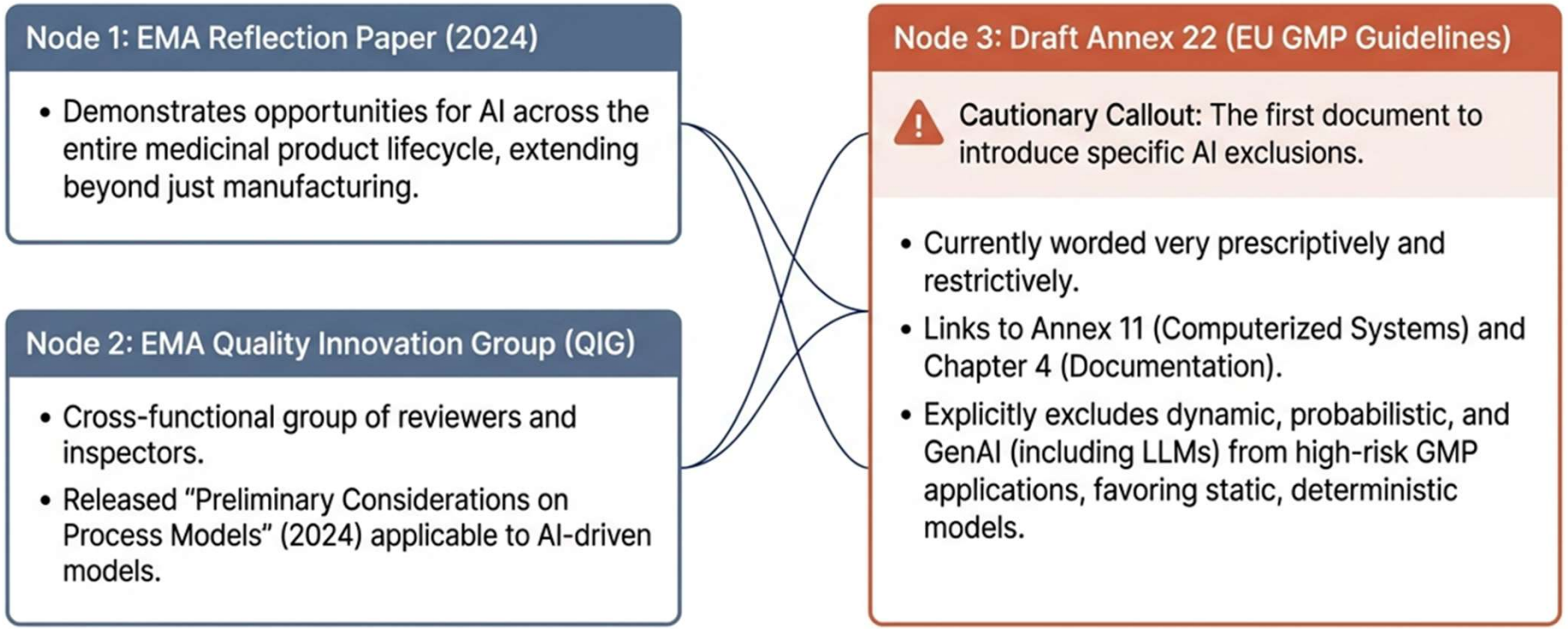
“The Spectrum” of AI and ML – Current Emerging Guidance Mapping

Different guidances address different parts of the spectrum – not yet aligned



FDA/EMA Guiding principles of good AI practice in drug development

AI/ML Recent Regulator's Interest - EMA



Spotlight on the US FDA and global bodies

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US FDA (CDER)

- Established the FRAME Initiative identifying AI in manufacturing as a priority.
- Draft Guidance (2025): "Considerations for the Use of AI to Support Regulatory Decision-Making."
- Discussion Paper (2023): "AI in Drug Manufacturing."

Joint EU/FDA Alignment

- Jointly published "Guiding Principles of Good AI Practice in Drug Development" (2026).
- **Note:** Shows positive alignment, though not specifically addressing manufacturing.

World Health Organization (WHO)

- Currently developing "Points to consider" guidance for inspectors on advanced manufacturing topics, including AI.

ICH

- QIG Chapter 5 provides a foundational risk framework regarding the criticality of different models in development and manufacturing.

Annex 22 and its potential impact on innovation with AI

- Industry in general expressed concerns about Annex 22 and its potential impact on AI in manufacturing and quality.
- Summary of feedback
  - **Main item:** Discouraging use of Large Language Models (LLM) and Generative AI (GenAI) in critical GMP applications (however no definition of "critical GMP applications", and overall discouraging of GenAI and LLM)
    - Risk approach should follow ICH Q9 methodology, which is not necessarily "dual choice" (Critical vs. non- critical)
  - *Additional concerning elements*
    - Document seen as very "prescriptive and restrictive" by industry
    - Example section 6: separate test data set- a statistical best practice but implemented very cumbersomely
    - Human in the Loop (HITL): Last section of document (HITL) ends with scenario where in some applications - each data point might have to be checked

Navigating AI-specific hazards

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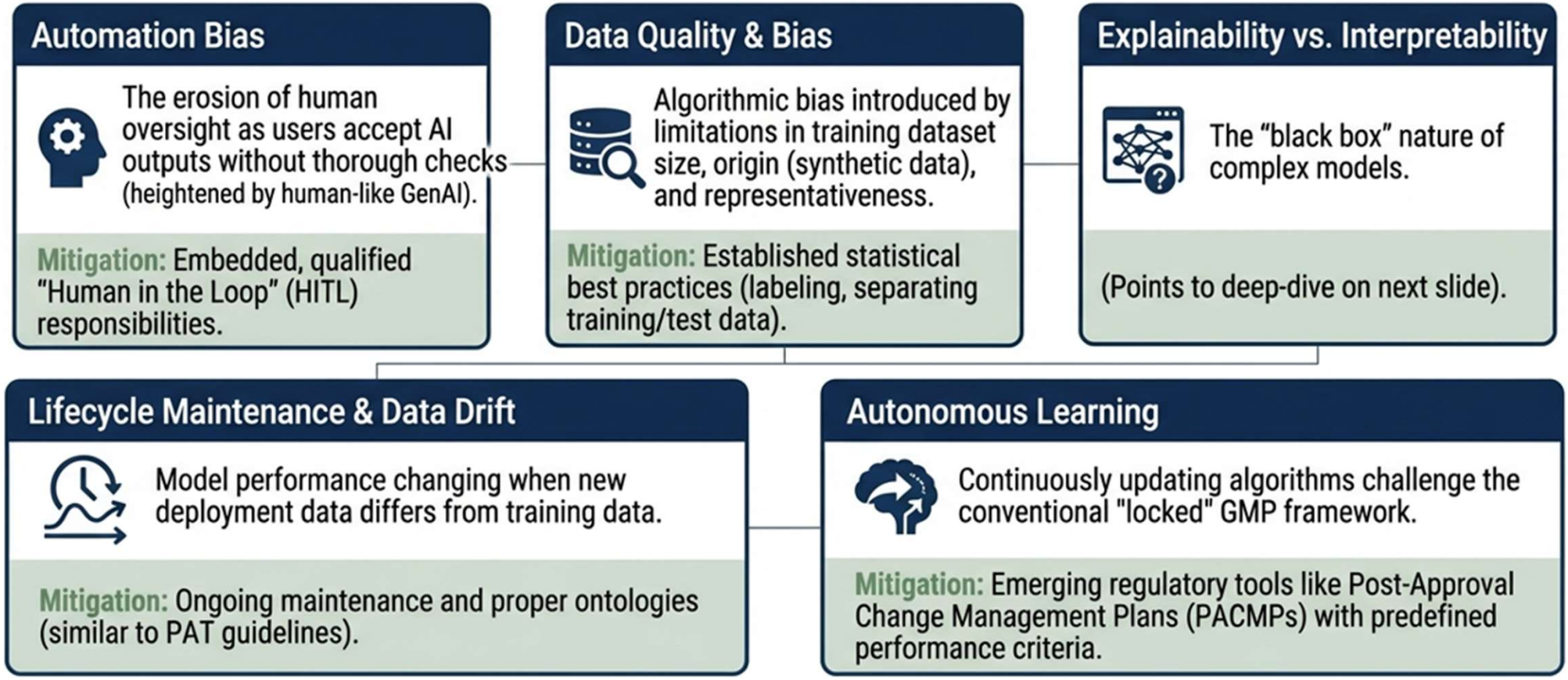

Explainability vs. Interpretability

Explainability (Overkill for GMP)

Definition: Understanding exactly why an AI system made a specific decision.

Origin: Rooted in systems making decisions based on personal or ethical data.

Challenge: The complex computational methodology of AI makes complete methodological transparency highly difficult.

Interpretability (The Practical Standard)

Definition: Understanding the meaning of an AI's output within a specific context.

Application: Perfectly suited for regulated pharmaceutical manufacturing.

Rationale: Manufacturing already relies on making quality decisions based on complex, established control systems. In this controlled environment, knowing what the output means is sufficient for safety and compliance.

The mindset shift – overcoming human hurdles

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Continuous Ecosystem Shift

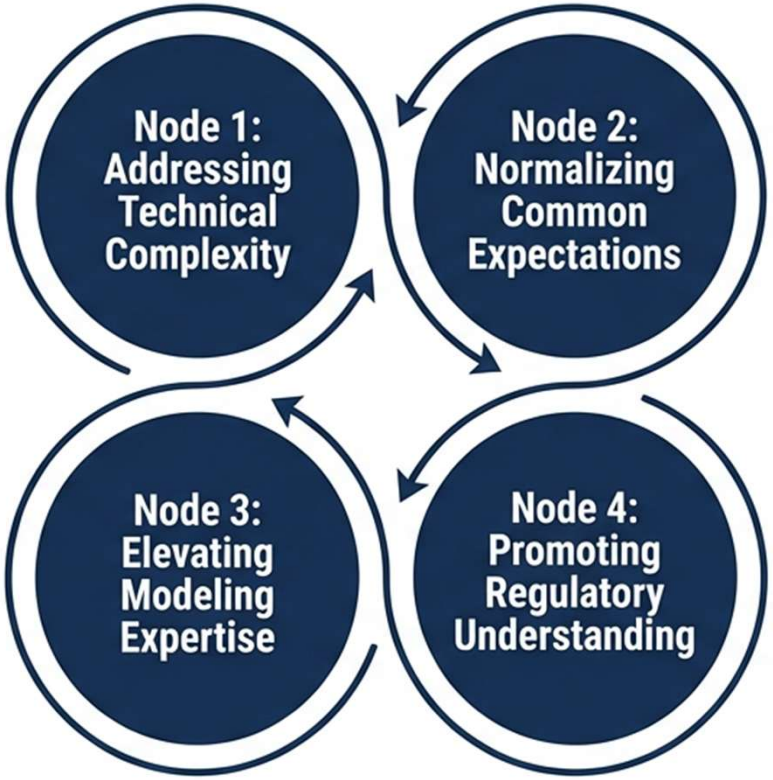
AI requires deep understanding to evaluate intended use during time-constrained inspections.

Solution: Comprehensive inspector training supported by industry expertise.

Continuous ecosystem shift

Current discussions over-rely on formalized Computer System Validation (CSV) (e.g., Annex 11).

Solution: Incorporate actual model development and point-of-use expertise rather than relying solely on formalistic "AI rules."



Continuous Ecosystem Shift

Regulators often apply higher, unfamiliar standards to digital solutions than to human solutions.

Solution: Accurately measuring human performance to set appropriate, equitable expectations for AI systems.

Continuous ecosystem shift

Lawmakers and NRAs must evaluate the credibility of AI outputs and risk control measures to form a science-based regulatory perspective.

The space shift – clinical vs. manufacturing

	Clinical / Patient AI	Manufacturing / CMC AI
Data Nature	Highly personal, medical, patient-specific.	Non-personal, operational, process-driven. ✓
Ethical & Privacy Risk	High risk (privacy, ownership, ethics, population bias).	Low risk; ethically unchallenging to process or store. ✓
Existing Governance	Requires complex new privacy and ethical frameworks.	Already strictly covered by robust technical and GMP compliance policies (e.g., data integrity). ✓

Regulatory policy must clearly distinguish "AI in manufacturing" from the rest of the medicinal lifecycle.

The imperative for global harmonization

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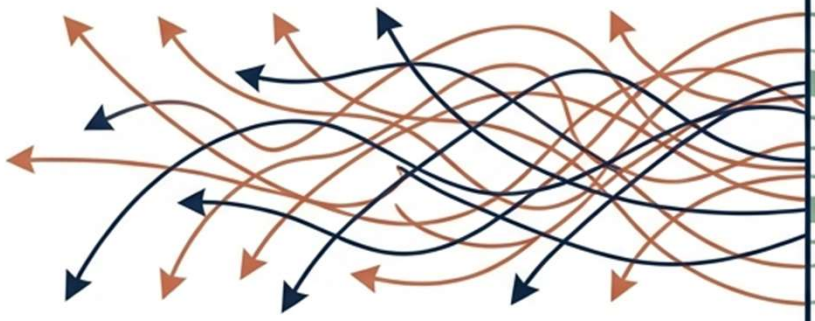
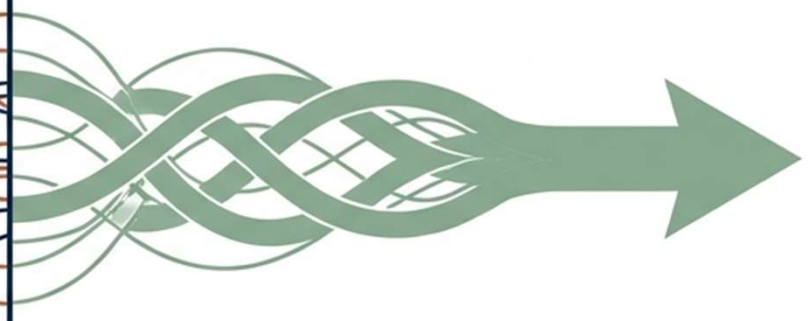
The Risk of Divergence



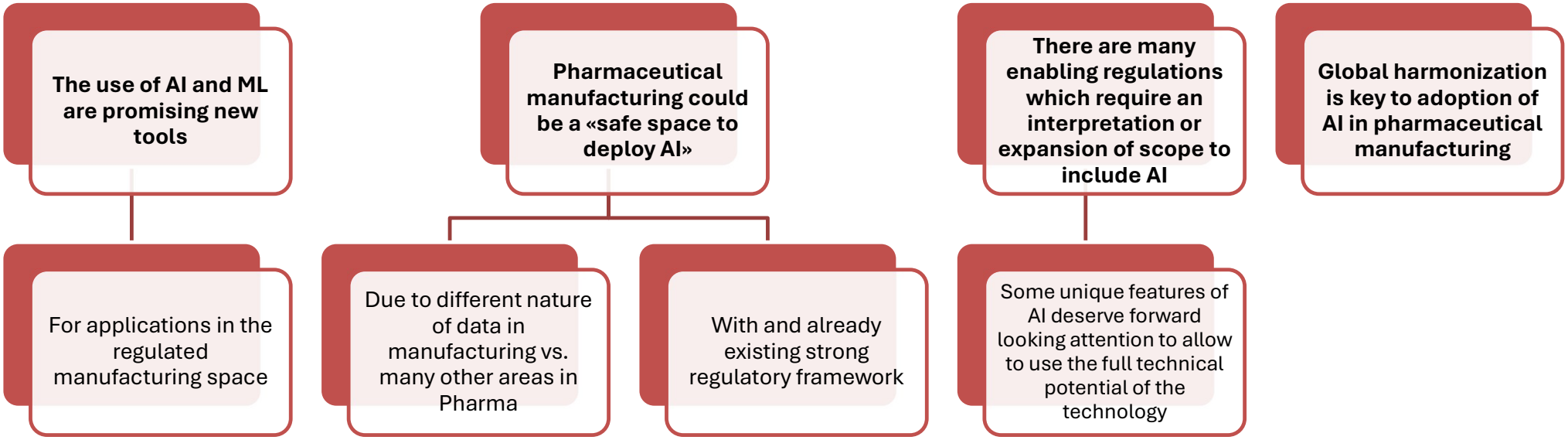
- Problem: Terminology is already diverging (e.g., EMA QIG dropping ASME V&V 40 terminology).
- Impact: Creates regulatory uncertainty, inconsistent expectations, and blocks the benefits to patients receiving identical products worldwide.

The Path to Convergence



- Action: Establish a globally aligned regulatory baseline and a harmonized glossary of terminology (e.g., defining "risk," "ethical AI," and "explainability" accurately for GMP).
- Mechanism: Guidelines (not rigid standards) developed by international regulatory authorities (like ICH) facilitate true convergence and consistent adoption.

Closing Remarks



Relevant resources

- EMA and FDA set common principles for AI in medicine development (US FDA EMA Joint statement)
- CDER's Framework for Regulatory Advanced Manufacturing Evaluation (FRAME) Initiative (The FRAME initiative)
- CDER 2025 draft guidance Considerations for the Use of Artificial Intelligence to Support Regulatory Decision-Making for Drug and Biological Products (US FDA CDER draft)
- New and revised guidelines planned for publication by CDER in 2026 - AI and ML Quality Considerations in Pharmaceutical Manufacturing (2026 CDER guidelines)
- EFPIA position paper on Application of AI in a GMP / Manufacturing environment- an Industry approach (2024 EFPIA paper)
- Artificial intelligence in pharmaceutical manufacturing – navigating innovation and regulation (2026 IFPMA position paper)

Acknowledgement

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Thank you
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