

# From Conventional to Intelligent: Ai-Driven Innovations in Clinical Pharmacy Practice

## Running Title: AI Innovations in Clinical Pharmacy

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Date of Submission: 10-02-2026

Date of Acceptance: 20-02-2026

### ABSTRACT

Background: Healthcare systems worldwide face mounting pressures—clinical, operational, and financial. Despite decades of evolution in clinical pharmacy practice, hospitals still grapple with weak decision support systems, alarmingly high medication error rates, inefficient workflows, inventory mismanagement, and gaps in patient monitoring. Much of this stems from workforce limitations and reliance on manual processes.

Aim: This review explores how artificial intelligence is reshaping clinical pharmacy practice. We examine AI's impact on medication safety, antimicrobial stewardship, inventory optimization, and personalized medicine, while also addressing the very real challenges of implementation.

Method: We conducted a narrative review of the literature, drawing on seminal and recent publications (2015-2025) alongside institutional case studies documenting real-world AI applications.

Findings: Artificial intelligence is no longer a futuristic concept—it's here, and it's transforming how pharmacists work. At Manipal Hospitals in India, IBM Watson for Oncology demonstrated 93% concordance with multidisciplinary tumor board recommendations, helping standardize cancer care across centers [8]. Mercy Health's Sepsis ImmunoScore™, now FDA-authorized, analyzes 22 clinical parameters to catch sepsis early enough to intervene [2]. At Mayo Clinic, an AI-powered ECG screening tool achieved 0.93 AUC for detecting silent ventricular dysfunction—something even experienced eyes might miss [3]. Indian tertiary hospitals using predictive inventory models cut stock-outs by 42% and reduced drug expiration by a third [4]. Meanwhile, Mount Sinai researchers published work in *Science* showing how machine learning can predict whether genetic variants will actually cause disease, using routine lab data from over a million electronic health records [9]. Another Mount Sinai AI model quadrupled delirium detection rates in hospitalized

patients, catching a condition that often goes unrecognized until it's too late [6]. Across these applications, a pattern emerges: AI doesn't replace clinical judgment—it sharpens it. When implemented thoughtfully, these systems reduce medication errors, improve diagnostic accuracy, optimize antimicrobial use, and free pharmacists to focus on what matters most: patient care.

Conclusion: The integration of AI into clinical pharmacy marks a fundamental shift from reactive to predictive practice. But technology alone isn't enough. Success demands clinical validation, transparency in how algorithms work, regulatory oversight, and most importantly, pharmacists who understand how to wield these new tools. The future isn't AI versus humans—it's AI working alongside humans, each amplifying the other's strengths.

**Keywords:** Artificial Intelligence; Clinical Pharmacy; Medication Safety; Machine Learning; Pharmacovigilance; Precision Medicine; Inventory Optimization

### I. INTRODUCTION

Clinical pharmacy has come a long way from its origins as a product-centered discipline. Today's clinical pharmacists focus on patients, not just prescriptions—optimizing therapies, preventing adverse events, and ensuring medications actually help rather than harm. But for all this progress, the systems surrounding hospital pharmacy practice remain stubbornly old-fashioned. Walk into almost any hospital pharmacy, and you'll see the same scene: pharmacists drowning in documentation, electronic health records that don't talk to each other, medication reconciliation done with pen and paper, and clinical decisions made with incomplete information. The consequences are real and sometimes devastating. A 2024 analysis found that nearly one in four hospitalized adults who died or ended up in intensive care had experienced a diagnostic error along the way. And medication-related harm? It's a

global epidemic, accounting for a staggering number of hospital admissions and billions in healthcare costs [21,24].The problem isn't lack of effort—it's the sheer volume of information. Laboratory results, imaging studies, pharmacogenomic data, clinical notes—it adds up to far more than any human can reasonably process. We've reached a point where the data exceeds our capacity to use it meaningfully. This is where artificial intelligence enters the picture. AI offers something different from traditional clinical decision support. Instead of simply firing off alerts based on rigid rules, AI can spot subtle patterns, predict deterioration before it happens, and give pharmacists the insights they need to intervene early. In this review, we'll explore how AI is quietly revolutionizing clinical pharmacy practice. We'll look at real-world implementations, examine what's working and what's not, and consider where we go from here. Throughout, one theme will emerge clearly: AI isn't about replacing pharmacists—it's about giving them superpowers.

## II. WHY CONVENTIONAL SYSTEMS KEEP FALLING SHORT

To understand why AI matters, we first need to appreciate the limitations of what we have now. Hospital systems today struggle with interconnected challenges that directly impact pharmaceutical care.

### 2.1 Decision Support That Often Gets in the Way

Traditional clinical decision support systems mean well, but they've become victims of their own success—or rather, their own enthusiasm. Rule-based alerts fire constantly. The result? Alert fatigue. Clinicians learn to ignore or override warnings because so many are irrelevant [7]. It's the digital equivalent of crying wolf. What we need isn't more alerts—it's smarter ones that understand context.

### 2.2 The Persistent Problem of Medication Errors

Despite decades of safety initiatives, medication errors remain stubbornly common. They happen when doctors prescribe, when nurses transcribe, when pharmacists dispense, when patients administer. Adverse drug events send hundreds of thousands of people to hospitals each year, and many are preventable [24]. We've built multiple layers of checking, but in busy clinical

environments, even the best double-check systems have limits.



Fig.1 Medication Errors

### 2.3 Workflows That Waste Precious Time

Ask clinical pharmacists what frustrates them most, and many will say the same thing: they spend more time on paperwork than on patients. Patient flow inefficiencies create treatment delays and longer hospital stays [1]. While pharmacists hunt down missing information or document what they've done, opportunities for meaningful clinical intervention slip away.

### 2.4 Inventory Management by Guesswork

Drug shortages and stock-outs shouldn't happen in modern hospitals, yet they do—regularly. Manual inventory tracking simply can't keep up with dynamic consumption patterns. Pharmacies order too much of some drugs (which eventually expire) and too little of others (leading to frantic emergency procurement). Patients bear the consequences when their medications aren't available.

### 2.5 Monitoring That Misses the Subtle Signs

With shortages of nurses and pharmacists, continuous patient monitoring is often more aspirational than actual. Subtle signs of deterioration—the kind that precede cardiac arrest or septic shock—get missed until they're no longer subtle. By then, the window for easy intervention has closed. These aren't isolated problems. They're systemic, interconnected, and deeply rooted in how healthcare operates. Which is precisely why we need solutions that are equally systemic—and intelligent enough to adapt.

### III. WHAT WE MEAN WHEN WE TALK ABOUT AI IN PHARMACY

Artificial intelligence sounds like a single thing, but it's really an umbrella term covering several related technologies. Understanding the differences matters because each has different applications in pharmacy.

Machine learning is the workhorse of modern AI. Instead of following explicitly programmed rules, machine learning algorithms learn from data. Show them enough examples of patients who developed adverse drug reactions, and they'll start recognizing the patterns that predict who's at risk. Supervised learning works with labeled data—we know which patients had reactions, so the algorithm learns to spot similar cases. Unsupervised learning finds hidden patterns we didn't know to look for, clustering patients or medications in ways that reveal new insights [23].

Deep learning takes machine learning further. Using multilayered neural networks inspired by the human brain, deep learning models can analyze incredibly complex data—images, waveforms, free text. When Mayo Clinic researchers built an AI that could detect heart dysfunction from an electrocardiogram, deep learning made it possible [3]. The patterns were too subtle for human eyes, but the neural network found them anyway.

Natural language processing bridges the gap between how humans communicate and how computers think. Much of the valuable information in medical records lives in physician notes—unstructured, variable, rich with meaning. NLP extracts that meaning, turning free text into structured data that AI systems can analyze [19]. For pharmacovigilance, this is revolutionary. Instead of waiting for voluntary adverse event reports, NLP can scan clinical notes in real-time and flag potential reactions as they're documented.

Predictive analytics combines statistical methods with machine learning to forecast what happens next. Will this patient deteriorate overnight? Is that medication likely to cause harm? Predictive models give pharmacists a glimpse into the future, creating opportunities for prevention rather than reaction [17].

These technologies don't work in isolation. Their real power emerges when they're combined—NLP extracting information from notes, machine learning finding patterns, predictive models flagging patients who need attention, and deep learning catching what human observers miss.

### IV. WHEN AI HELPS MAKE BETTER CLINICAL DECISIONS

Of all AI's potential applications, improving clinical decision-making may be the most immediately valuable. And some of the most compelling evidence comes from oncology, where treatment decisions are complex and consequences profound.

#### 4.1 The Manipal Experience: IBM Watson for Oncology

India faces an oncologist shortage even as cancer rates rise. At Manipal Hospitals, they turned to IBM Watson for Oncology (WFO) to help bridge the gap. But before trusting AI recommendations, they needed to know: would Watson agree with their own experts?

The results, published in *Annals of Oncology*, were striking. When researchers compared Watson's treatment recommendations against Manipal's multidisciplinary tumor board decisions for 1,000 consecutive cancer patients, they found 93% concordance for breast cancer cases [8]. For colorectal cancer, a double-blind study showed initial agreement of 87%, rising to 95% after second review [5]. The AI wasn't just matching human experts—in some cases, it was suggesting options the tumor board hadn't considered, drawing on a broader database of global oncology literature. What made this work wasn't the AI alone, but how it was used. Manipal's oncologists didn't blindly follow Watson's recommendations. They used them as a second opinion, a check on their own thinking, a way to ensure they hadn't missed something. The AI standardized care across centers, helped less experienced oncologists make better decisions, and ultimately supported—not replaced—clinical judgment. Beyond oncology, AI-enhanced CDSS platforms like VisualDx, Isabel Healthcare, and Epic's sepsis model are proving their worth across medicine. Unlike rule-based systems that fire indiscriminately, these ML-powered tools adapt to individual patient data, learning what's relevant and what's not [18].



**Fig. 2 Use of IBM Watson AI**

For clinical pharmacists, this means decision support that actually supports. When you're adjusting a complex medication regimen, AI can flag potential interactions, suggest dose modifications based on renal function, or identify patients who might benefit from pharmacist review. It's like having a second pair of eyes that never tires and never forgets.

## V. CATCHING PROBLEMS BEFORE THEY HAPPEN: AI-POWERED MEDICATION SAFETY

Medication safety has always been about prevention—stopping errors before they reach patients. AI takes this to a new level by predicting risk before harm occurs.

### 5.1 Spotting Sepsis Early at Mercy Health

Sepsis kills quickly. By the time obvious symptoms appear, patients may already be crashing. Mercy Health System in the United States wanted to change that, so they implemented an AI-based Sepsis ImmunoScore™.

The tool analyzes 22 clinical parameters continuously—vital signs, lab values, subtle trends that human observers might miss. When patterns suggest impending sepsis, it alerts the care team. In 2024, Prenosis, the company behind the tool, received FDA authorization based on data from 10 study sites nationwide. Mercy Research alone contributed 30,000 blood samples to the research. According to Dr. Ashok Palagiri at Mercy Virtual, "This clinical trial and research is essential in spotting sepsis early" [2]. The impact extends beyond sepsis. Similar AI models have shown they can optimize treatment strategies for ICU patients [10], with one study demonstrating that deep learning surveillance systems reduce serious

medication errors by up to 40% in hospital settings [13].

### 5.2 Mining Notes for Adverse Reactions

One of pharmacy's persistent challenges is pharmacovigilance—catching adverse drug reactions after they occur. Voluntary reporting captures only a fraction of events. But natural language processing changes the game. Instead of waiting for someone to file a report, NLP systems scan clinical notes in real-time, flagging mentions of symptoms that might represent ADRs [19]. When a physician writes "patient developed rash after starting antibiotic," the system notices. When a nurse documents "confusion possibly medication-related," the system adds it to the database. Suddenly, adverse event surveillance becomes proactive rather than reactive. For clinical pharmacists, this means earlier identification of problematic medications, faster intervention when reactions occur, and better data for preventing future events.

## VI. SMARTER INVENTORY MANAGEMENT: WHEN AI PREDICTS WHAT YOU'LL NEED

Drug supply chains are notoriously unpredictable. Seasonal demand spikes, manufacturer shortages, sudden shifts in prescribing patterns—any of these can leave pharmacies scrambling.

### 6.1 The Indian Tertiary Hospital Experience

Kushwaha's 2025 study in Indian tertiary hospitals demonstrates what's possible with AI-driven inventory management. Using Gradient Boosting and LSTM algorithms, researchers built predictive models that forecast medication demand with remarkable accuracy.

The results speak for themselves: stock-outs dropped by 42%. Expired drugs—money literally thrown away—decreased by 33%. Emergency purchases, those panic buys at inflated prices, fell by 27%. Forecasting error improved from nearly 19% down to just under 8% [4].

How does it work? The AI considers seasonal disease patterns—more respiratory medications in winter, more allergy drugs in spring. It analyzes prescribing behavior, learning which physicians prefer which medications. It accounts for supplier variability, knowing which vendors deliver reliably and which don't. All this information feeds into predictions that help

pharmacists order exactly what they need, when they need it.

Global platforms like SAP Healthcare AI and McKesson Supply Chain AI are now offering similar capabilities. For hospital pharmacists, this means fewer treatment interruptions, less waste, and more reliable patient care.

## VII. BEYOND TRADITIONAL PHARMACY: AI IN GENETIC RISK AND DELIRIUM DETECTION

Sometimes the most exciting AI applications come from unexpected places. Two recent Mount Sinai studies illustrate how AI breakthroughs in other domains have profound implications for pharmacy.

### 7.1 Predicting Genetic Destiny

We've long known that certain genetic variants increase disease risk, but predicting whether a specific variant will actually cause disease in a specific person has been maddeningly difficult. Most variants are classified as "variants of uncertain significance"—medical jargon for "we have no idea."

Mount Sinai researchers tackled this problem with machine learning. Published in *Science* [9], their model combines genomic data with clinical information from over a million electronic health records. By analyzing what actually happened to people with specific variants, the AI learned to predict "penetrance"—the likelihood that a variant would lead to disease. For more than 1,600 genetic variants, the model calculated "ML penetrance" scores. Higher scores meant greater probability of disease development. Variants previously labeled uncertain suddenly had meaningful risk estimates. For clinical pharmacists, this is transformative. When a patient's genetic test shows a variant of uncertain significance for a condition that affects drug metabolism or disease risk, pharmacists can now make more informed recommendations. The uncertainty isn't gone, but it's quantified—and that matters.

### 7.2 Catching Delirium Before It's Too Late

Delirium in hospitalized patients is dangerous, common, and frequently missed. Patients become confused, agitated, or withdrawn, and busy nurses and doctors may not notice until the condition is advanced. Another Mount Sinai team built an AI model to change this. Published in *JAMA Network Open* [6], their system analyzes both structured data and clinical notes, using

machine learning to identify patients at high delirium risk. In a study of more than 32,000 patients, monthly delirium detection rates jumped from 4.4% to 17.2%—quadrupling identification of this dangerous condition. According to senior author Joseph Friedman, MD, "Our model isn't about replacing doctors—it's about giving them a powerful tool to streamline their work" [6]. For pharmacists, this matters because delirium often has medication-related causes or consequences. When the AI flags a high-risk patient, pharmacists can review their medication regimen, adjust doses of deliriogenic drugs, and recommend alternatives. Early identification creates opportunities for prevention that simply didn't exist before.

## VIII. SMART WORKFLOW MANAGEMENT

Nobody goes into pharmacy to spend hours on documentation. Yet that's exactly what happens in most hospitals. AI-based workflow platforms like Qventus and LeanTaaS (iQueue) aim to change that by optimizing patient flow and reducing administrative burden. Research shows that AI-supported patient flow management reduces length of stay and improves bed utilization [1]. When pharmacists spend less time chasing down information or documenting routine tasks, they have more time for clinical consultation, antimicrobial stewardship, and direct patient interaction. The goal isn't to automate pharmacists out of existence—it's to automate the boring stuff so pharmacists can do what only humans can do: think critically, communicate compassionately, and make nuanced clinical judgments.

## IX. SUPPORT IN EVIDENCE-BASED PRACTICE

Keeping up with medical literature is impossible. Thousands of studies are published every day. No human can read them all, let alone synthesize them into practice. AI literature synthesis tools are beginning to help. They scan new publications, extract relevant findings, and alert clinicians to studies that might change practice. For pharmacists trying to stay current while managing daily responsibilities, this is invaluable.

The Mayo Clinic AI-enabled ECG study demonstrates another dimension of evidence generation. By training a deep learning model on 44,000 ECG-echocardiogram pairs, researchers created a tool that could detect asymptomatic left ventricular dysfunction from ECG alone—something previously impossible [3]. The AI found

patterns that had been hiding in plain sight for decades, generating new knowledge that now improves patient care. For pharmacists, this means more accurate diagnosis of conditions that affect medication management, and earlier identification of patients who might benefit from specific therapies.

#### X. PERSONALIZED MEDICINE: WHERE AI MEETS PHARMACOGENOMICS

The promise of personalized medicine has always been tantalizing: give the right drug to the right patient at the right dose. Pharmacogenomics gets us partway there, telling us which genetic variants affect drug metabolism. AI takes us further, integrating genetic data with everything else we know about patients.

Pharmacogenetic-guided dosing for warfarin, clopidogrel, and other drugs has already improved safety and efficacy [11]. Machine learning models in oncology can predict which patients will experience chemotherapy toxicity and which are likely to respond to specific agents [12].

The Mount Sinai genetic penetrance work adds another layer [9]. When a patient carries a variant that might affect drug metabolism—but the significance is uncertain—AI risk scores help pharmacists make better decisions. Should you treat this patient as a poor metabolizer, or is the variant likely benign? The AI doesn't give a definitive answer, but it provides probabilities that inform clinical judgment.

Personalized medicine, powered by AI, is moving from aspiration to reality. For clinical pharmacists, this means moving beyond one-size-fits-all dosing toward truly individualized therapy.

#### XI. THE COMPLICATED ETHICS OF AI IN HEALTHCARE

For all its promise, AI in healthcare raises legitimate concerns that can't be ignored.

**The black box problem** is perhaps the most troubling. Many AI models, particularly deep learning systems, can't explain why they reached a particular conclusion. They're right a lot of the time, but when they're wrong, understanding why is nearly impossible. For clinicians who must take responsibility for patient outcomes, this opacity is deeply uncomfortable.

**Data privacy** becomes more complex when AI systems train on millions of patient records. Even de-identified data can sometimes be

re-identified, and the consequences of a breach grow with the scale of data collected.

**Algorithmic bias** is a well-documented problem. AI models trained primarily on data from one population may not perform well on others [16]. If a sepsis prediction model was developed using data from mostly white patients, will it work as well for Black or Hispanic patients? Sometimes yes, sometimes no—and often we don't know until it's too late.

**Accountability** becomes murky when AI is involved. If a clinician follows an AI recommendation and the patient is harmed, who's responsible? The clinician who made the final decision? The hospital that implemented the system? The developers who built the model? Clear frameworks are still emerging.

The FDA has begun addressing these issues through its AI/ML-based Software as a Medical Device action plan [14]. The Sepsis ImmunoScore™ authorization represents an early example of regulatory oversight for clinical AI tools. But regulation alone isn't enough. As Mount Sinai researchers note, validation across diverse populations and healthcare systems remains essential [9].

**Skill gaps** are perhaps the biggest barrier. Most pharmacists have never been trained to work with AI tools. They don't understand how the models work, what their limitations are, or how to integrate them into practice. Educational reforms that embed AI training in pharmacy curricula are essential [2].

**Infrastructure costs** can be prohibitive. Implementing AI requires not just software licenses but integration with existing EHRs, data standardization, and ongoing maintenance. For resource-constrained hospitals, these costs may be insurmountable.

**Data fragmentation** means that even when hospitals want to implement AI, their data may not be ready. Disparate systems that don't talk to each other, inconsistent documentation practices, missing information—all of these undermine AI performance.

Regulatory uncertainty makes some organizations hesitant to invest. If approval pathways are still evolving, if liability questions remain unanswered, if standards haven't been established, waiting may seem safer than moving forward.

## XII. CONCLUSION

Artificial intelligence is transforming clinical pharmacy practice in ways that were unimaginable a decade ago. At Manipal Hospitals, AI treatment recommendations match tumor board decisions 93% of the time, helping standardize cancer care across a vast and diverse country [8]. At Mercy Health, FDA-authorized AI catches sepsis early enough to save lives [2]. At Mayo Clinic, deep learning finds heart dysfunction hiding in plain sight on routine ECGs [3]. In Indian tertiary hospitals, predictive inventory systems cut drug shortages nearly in half [4]. At Mount Sinai, machine learning predicts genetic disease risk [9] and quadruples detection of hospital delirium [6].

What ties these stories together is not technology alone, but how that technology is used. In every case, AI serves as an augmentative tool—amplifying human intelligence rather than replacing it. The 93% concordance rate doesn't mean Watson should practice oncology alone. It means oncologists have a powerful second opinion. The quadrupled delirium detection rate doesn't replace nursing assessment. It means nurses know which patients need closer attention.

The shift from reactive to predictive pharmacy practice is real and accelerating. But technology doesn't drive this shift by itself. It takes pharmacists who understand AI's capabilities and limitations. It takes institutions willing to invest in implementation. It takes regulators creating frameworks that protect patients without stifling innovation. And it takes ongoing research validating that these tools work for everyone, not just the populations where they were developed.

The future of clinical pharmacy lies at the intersection of human expertise and artificial intelligence. Not AI alone. Not humans alone. Both together, each amplifying the other's strengths. That's not just the future—it's already beginning.

**Conflict of Interest Statement:** The authors declare no conflicts of interest.

**Funding Statement:** This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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