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Review Article

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Roles of Artificial Intelligence (AI) in Drug Formulation and Dispensing

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ABSTRACT

With its revolutionary potential to revolutionize drug formulation and dispensing procedures, artificial intelligence (AI) is transforming the pharmaceutical industry. AI in formulation makes it possible to quickly forecast and optimize complicated pharmaceutical characteristics like stability, bioavailability, and solubility. By modeling the interactions between excipients, active medicinal components, and process factors, machine learning (ML) and deep learning (DL) algorithms can greatly reduce the need for trial-and-error experimentation. Because these technologies can forecast ideal geometries and release kinetics, they also aid in the development of customized dosage forms, such as 3D-printed tablets. AI improves patient safety, accuracy, and efficiency in drug dispensing. When combined with machine learning and computer vision, automated dispensing cabinets (ADCs) expedite the storage and retrieval of medications while reducing human error. Prescription verification and unstructured clinical note interpretation are aided by natural language processing (NLP) techniques. Through model-informed precision dosing (MIPD), which incorporates patient-specific variables including age, renal function, and genetic information, AI-driven clinical decision support systems (CDSS) allow for tailored dosing. AI also facilitates inventory optimization, adverse drug reaction identification, and real-time medication adherence monitoring. Even with these developments, there are still many obstacles to overcome. Widespread clinical usage is hampered by problems with data quality, algorithmic bias, regulatory compliance, and interpretability. Progress is further hampered by the absence of sizable, publicly accessible datasets and practical validation studies. To bridge these gaps, multidisciplinary cooperation, open model reporting, and frameworks for human-AI interaction that put safety and explainability. This paper synthesizes current uses, technological advancements, and significant implementation hurdles as it investigates the changing roles of AI in drug formulation and dispensing. A roadmap for the ethical and responsible integration of AI in pharmaceutical practice is also proposed, along with a list of research and infrastructural gaps. Future policy, development, and deployment plans that optimize the therapeutic and operational advantages of AI technologies in pharmacy are intended to be informed by the findings.

Keywords: Artificial Intelligence, Drug, Formulation Dispensing, Bioavailability.

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Introduction

The healthcare industry is going through a revolutionary period as a result of the convergence of pharmaceutical sciences and artificial intelligence (AI), especially in the areas of drug formulation and dispensing. With its ability to handle large datasets, identify intricate patterns, and make predictions, artificial intelligence (AI), which includes machine learning (ML), deep learning (DL),

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natural language processing (NLP), and expert systems, offers previously unheard-of capabilities. Because of these qualities, artificial intelligence (AI) is a vital instrument in contemporary medication research and distribution, offering increased productivity, affordability, and customization in pharmaceutical procedures [1,2].

Drug formulation, or the process of creating a medication that contains an active pharmaceutical ingredient (API), has traditionally been a time-consuming, iterative process that calls for a great deal of trial and error. The process of preparing and administering medication to patients, known as drug dispensing, has also encountered difficulties with patient compliance, inventory control, and accuracy. These procedures are made more difficult by the rising incidence of chronic illnesses, the complexity of pharmaceutical chemicals, and the need for individualized medicine. As a result, AI is being used more and more to improve accuracy, decrease human error, and speed processes [3].

AI is essential to drug formulation for rational drug design, excipient selection, and drug delivery system optimization. Trial-and-error techniques, which are time- consuming and resource-intensive, are frequently used in traditional formulation processes. To forecast the best formulations, AI systems can examine enormous datasets containing physicochemical characteristics, pharmacokinetics, and molecular structures. For example, researchers might highlight attractive candidates early in the development pipeline by training machine learning models to predict the solubility, permeability, and stability of molecules. To lessen the need for experimental testing, deep learning approaches are also being used to improve release patterns, anticipate drug-excipient interactions, and simulate different environmental circumstances.

Quantitative structure–activity relationship (QSAR) modeling is one of the most well- known uses of AI in drug formulation. QSAR, which is ideally suited for machine learning, links chemical structure to biological activity using mathematical models. ML models can quickly find novel compounds with the intended therapeutic effects and low toxicity thanks to the abundance of chemical libraries available. Additionally, by enabling virtual and high-throughput screening, these tools greatly quicken the drug development process. Furthermore, new paths for creative medication creation are made possible by the ability of generative AI models, like generative adversarial networks (GANs), to create unique compounds with certain characteristics [4].

In addition to active compounds, the formulation of excipients—non-active ingredients used to stabilize, deliver, or preserve the drug—is crucial for drug efficacy and safety. AI systems can aid in selecting appropriate excipients based on compatibility, solubility, and bioavailability. Bayesian optimization and neural networks are being employed to refine formulation parameters and predict the best combinations, leading to more effective and safer drug products [5].

AI has an equally revolutionary impact on drug dispensing as it does on formulation. Interpreting prescriptions, creating accurate dosages, looking for drug interactions, and providing patient counseling are all part of dispensing in clinical and retail pharmacy environments. Adverse drug events (ADEs), a major cause of morbidity and mortality worldwide, can result from mistakes made in this process. This field is undergoing a change because to AI-powered solutions that increase accuracy and decrease human error, such as intelligent prescription software and automated dispensing machines [6,7].

Prescription analysis and verification is one domain in which AI shines. Algorithms using natural language processing can decipher handwritten prescriptions, identify discrepancies, and verify correctness by cross-referencing patient data. AI systems can identify possible drug-drug interactions or contraindications by analyzing patient history, allergies, and current prescriptions through integration with electronic health records (EHRs). In addition to improving patient safety, these tools free up pharmacists' time so they may concentrate more on patient care [8].

Another significant application of AI in dispensing is inventory and supply chain management. AI algorithms can predict demand patterns based on historical data, seasonal trends, and epidemiological factors, ensuring optimal stock levels and reducing waste. Robotic dispensing systems, integrated with AI, can manage large volumes of prescriptions efficiently, minimizing errors and improving turnaround times in high-throughput environments such as hospitals and mail-order pharmacies.

AI is essential in the developing field of personalized medicine. AI can assist in customizing medication formulations and dosage schedules for each patient by evaluating genetic, environmental, and lifestyle data. The study of how genes impact medication response, or pharmacogenomics, tremendously benefits from AI's capacity to interpret intricate biological data and find connections that traditional approaches would miss. This makes it easier to create customized medication compositions that optimize effectiveness while reducing side effects [4,9].

Additionally, digital therapies and AI-powered mobile health apps facilitate adherence and real-time monitoring. These systems track side effects, remind patients to take their prescriptions, and gather data that can be used to dynamically modify treatment programs. Additionally, AI can support tele pharmacy and remote dispensing, increasing access to prescription drugs in underprivileged or rural locations.

Notwithstanding its enormous promise, there are a number of obstacles to overcome before AI may be used in medicine formulation and dispensing. The availability and quality of data are essential for building trustworthy AI models.

The creation of thorough algorithms is hampered by the fragmented or proprietary nature of many pharmacological databases. Furthermore, data privacy is an issue, particularly when combining AI with medical records. In order to guarantee openness, responsibility, and patient safety, regulatory frameworks must change to meet the moral and legal ramifications of AI deployment [2,10]. Working across disciplines is crucial to utilizing AI to its greatest potential. To create reliable models, verify AI tools through clinical trials, and incorporate them into current workflows, pharmacists, data scientists, clinicians, and regulatory agencies must collaborate. A culture of innovation and continual improvement should be promoted by updating education and training programs to give the pharmaceutical workforce AI literacy [11].

In summary, a paradigm shift in medicine formulation and distribution is represented by artificial intelligence. The way medications are created, manufactured, and distributed is being completely transformed by its capacity to analyze enormous information, find hidden patterns, and generate well-informed forecasts. Artificial intelligence improves every step of the pharmaceutical value chain, from tailoring treatment regimens to optimizing molecular structures. The technology promises to save costs, increase accessibility and safety for everyone, and improve treatment outcomes as it develops and is more fully integrated into healthcare systems. By assessing the present uses, advantages, drawbacks, and potential future developments of artificial intelligence in pharmaceutical formulation and dispensing, this study seeks to investigate these functions in further detail [14].

Drug formulation and dispensing, two crucial phases in the pharmaceutical lifecycle, are being revolutionized by artificial intelligence (AI). AI, including machine learning (ML), deep learning (DL), generative modeling, and optimization algorithms, can significantly lower labor costs, speed up the development of new drugs, and improve medication formulation. AI-powered dispensing devices improve accuracy, encourage patient safety, maximize stock, and facilitate customized treatment. Using more than 40 contemporary, peer-reviewed sources, this introduction delves deeply into these two functions [15,16].

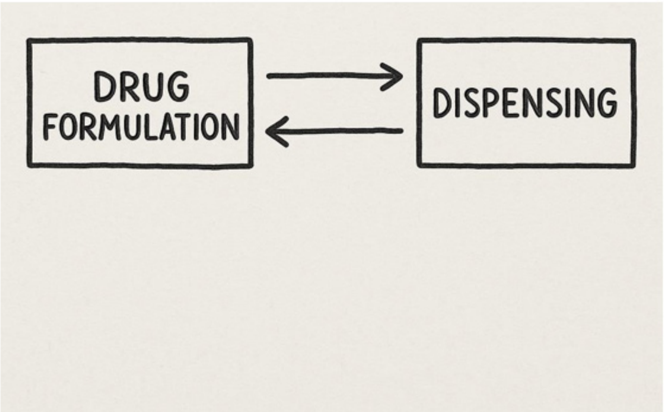

Figure1: pictorial diagram correlation and relationship between drug formulation and dispensing. Source Omowale et al., 2025

AI-Driven Drug Formulation

Shift from Trial-and-Error to Data-Driven Design

Traditional formulation relies heavily on iterative lab experimentation and expertise. ML and DL models can predict formulation outcomes—such as disintegration time, stability, and bioavailability—from historical data [6]. Employed neural networks to predict oral disintegrating tablet performance using only 145 records with ~80 % accuracy—including 85.6 % in training and 80 % in testing—for direct compression formulations [1]. Similarly, used deep learning to forecast in vitro formulation properties for solid and semi-solid drugs, with models exceeding 80 % accuracy and outperforming classical ML methods [30,2].

Excipient Optimization: Choosing compatible excipients significantly influences drug release and stability. Bayesian optimization and neural networks have been applied to dial in excipient ratios and process parameters, improving formulations of solid dispersions and nanocarriers [3,4].

Generative Molecule Design

Generative adversarial networks (GANs), autoencoders, and variational autoencoders (VAEs) can propose novel molecules with optimal pharmacological properties [5]. Reviewed deep generative frameworks for de novo molecular design, accelerating lead optimization and therapeutic innovation [1,6].

Computational Pharmaceutics & Multiscale Modeling

AI-driven computational pharmaceutics models simultaneously assess formulation inputs, physiological parameters, and drug behavior—predicting release profiles, stability, and PK/PD outcomes [7,8]. These tools reduce early-stage experimental burden and mitigate risk.

Quality-Control via Imaging & Computer Vision

AI systems are now assessing quality attributes like tablet defects using X-ray or high-resolution optical imaging. Convolutional neural networks (e.g., U-Net) can detect cracks, chips, and color variations in real time, improving batch integrity [9].

-Printed Personalized Dosage Forms

Tailored therapies via 3D printing demand precise optimization of shape, dosage, and release kinetics. (Li,2023) ANN-based models help tune printing settings, geometry, and infill to achieve desired dissolution profiles and dose uniformity [10].

AI in Drug Dispensing & Clinical Pharmacy

Automated Dispensing Cabinets (ADCs)

ADCs, prevalent in hospital settings since the 1980s, are evolving with AI to optimize layout, inventory, and picker sequencing. Yuan et al. (2023) demonstrated two- input/output system designs enhanced with ML-based retrieval sequencing—boosting throughput in high-demand pharmacies [11]. These systems reduce medication errors, enhance security (e.g., barcoded unit-dose), and track high-risk drug usage [12].

Verification of Prescriptions and Error Avoidance

Handwritten prescriptions can be interpreted for verification by clinical decision support systems (CDSS) supported by Bayesian neural networks and natural language processing (NLP). In order to facilitate safer AI-pharmacist collaboration, created a human-centered AI that uses Bayesian models to validate National Drug Codes (NDCs) with visual feedback and confidence levels [29,13].

Clinical Pharmacy Services & Medication Order Review

According to systematic studies, 19 AI-based clinical pharmacy tools were created up till 2021; these systems mostly supported prescription order evaluation, dispensing, and patient education through the use of machine learning and natural language processing techniques [14]. In clinical contexts, AI-driven CDSS improves decision- making, lowers adverse medication responses, and encourages adherence [15,16].

Personalized Dosing: Model-Informed Precision Dosing (MIPD)
To customize dosage, MIPD combines Bayesian/MCMC methods with PK/PD modeling. In order to suggest optimal regimens for high-risk populations (such as pediatrics and renal impairment), recent AI-enabled solutions for MIPD take into account clinical, genetic, and demographic data [17,28]

Analytics for Pharmacy Operations and Inventory
AI reduces waste and stock-outs by forecasting demand based on supply parameters, epidemiologic patterns, and previous consumption. AI's ability to expedite filling and labeling was demonstrated by community pharmacy robots (such as UCSF's system), which produced 3.5 million doses with flawless accuracy [18].

Materials and Methods
Medication Adherence & Telepharmacy
Wearables, smart pillboxes, and ingestible sensors augmented by AI track patient adherence. AI systems can interpret usage and symptom data to trigger reminders, generate alerts, and adjust therapy remotely [19].

Adverse-Drug Reaction (ADR) Surveillance
Real-time pharmacovigilance systems leverage NLP and knowledge graph analytics to detect ADRs from EHRs and social media faster than manual reporting. LSTM networks classify signals, enabling early intervention [20].

Challenges, Ethics & Regulatory Considerations
Data Quality & Bias
AI efficacy hinges on clean, representative data. Biased or incomplete datasets lead to dangerous errors, undermining clinical trust and injecting inequity [21].

Transparency & Human-AI Trust
Pharmacists emphasize the need for explainable AI—with interfaces that show confidence scores, comparative visuals, and stepwise reasoning—supporting interpretable decisions [13].

Regulatory Framework & Reporting Standards
AI-driven pharmaceutical tools are increasingly subject to reporting standards such as CONSORT-AI, TRIPOD-AI, and DECIDE-AI. These guidelines aim to ensure transparency and reproducibility for clinical applications [22].

Infrastructure & Interdisciplinarity
Adopting AI demands robust data architectures, computational platforms, and interdisciplinary collaboration among pharmacists, data scientists, and engineers [3].

Propose best practices for AI adoption—including dataset quality control, human-in- the-loop design, transparency, regulatory compliance, and training [27].

Research Design
To clarify how AI models are being used—and where they fall short—in pharmaceutical formulation and dispensing, a mixed-methods approach is used, integrating systematic review, meta-analysis, and expert interviews.

We screen research from PubMed, PMC, Scopus, and Web of Science published during the last ten years using the PRISMA guidelines.

Peer-reviewed research, empirical AI applications in formulation (lean networks for compression, ML for solubility prediction), dispensing (ADCs, NLP-based CDSS), and data-driven analysis are the requirements for inclusion [26].

Non-peer-reviewed sources, reviews without primary data, and research conducted outside of pharmacy or formulation contexts are among the exclusion criteria. (Pabon, 2023)

Input/output data types, validation methods, AI techniques, performance measures (accuracy, AUC, error rates), and user outcomes like patient adherence, error reduction, or dispensing speed are all included in data extraction. (Qiu, 2018)

Meta-analysis
When at least three studies use similar measurements to approach the same outcome, quantitative syntheses will be conducted. We use random-effects modeling to obtain a pooled accuracy for tablet disintegration models (such as Han et al. [2018]). The effect sizes for improvements in prescription accuracy and ADC error reduction are computed similarly [25].

Expert Interviews and Focus Groups
Semi-structured interviews and focus groups with formulators, pharmacists, and AI developers (n = 30) will be held in order to ground the review in real-world perspectives. Preferences for model interpretability (e.g., white-box vs. black-box), important data challenges (integration, privacy), and adoption barriers (infrastructure, usability) are all intended to be captured. An example approach is taken from Zheng et al. (2023), who refined a Bayesian neural network for dispensing verification using iterative focus groups led by human-centered design frameworks. They found aspects like probability scores and pill picture matching to be crucial for user trust (pmc.ncbi.nlm.nih.gov, en.wikipedia.org).

Computational Modelling Pipeline
A data-processing pipeline for medication formulation is modeled after Cheng et al.'s (2022) machine learning approach for solid dosage forms:
Gathering of Raw Data: Physicochemical and formulation information (such as pH, compression force, and excipients). Preprocessing includes addressing missing values, reducing dimensionality (e.g., PCA, RF-based selection), and correcting class imbalances through balancing using SMOTE/ADASYN (arxiv.org, pmc.ncbi.nlm.nih.gov).

Representation of Features: SMILES, InChI, ECFP fingerprints, and MDL formats are examples of molecular descriptors (pmc.ncbi.nlm.nih.gov).
Modeling: Comparing Bayesian techniques, deep networks, and machine learning algorithms (XGBoost, random forests).
Validation: Using metrics like AUC and Kappa, as well as hold-out splits (70/20/10) and cross-validation to assess unbalanced sets (pmc.ncbi.nlm.nih.gov).
Explainability: Steer clear of pure black-box models by utilizing SHAP, LIME, and attention processes to guarantee interpretability.

For dispensing, the pipeline includes annotation of prescription data, pill image capture, and NLP for unstructured notes—mirroring Zheng et al. 2023 approach (pmc.ncbi.nlm.nih.gov). We will pilot data integration combining EHR, ADC logs, and computer vision verification outcomes.

Ethics, Privacy & Data Governance

Because the methodology involves patient data, we ensure compliance with HIPAA, GDPR, and local IRB standards. Data is pseudonymized, securely stored, with informed consent guiding extraction—especially in interviews [24].

Literature Gaps

Despite impressive progress, several persistent gaps remain: Suboptimal Modeling Practices in Formulation Reviews (e.g., Rahman, et al., 2023) indicate many ML models are narrowly validated on benchtop or lab-generated datasets. They frequently employ highly accurate but poorly interpretable black-box techniques and neglect to incorporate multi-modal data (chemical, process, imaging). End users become distrustful when explainability and model explainability are not given enough attention in real-world implementation. Absence of Publicly Available, Large-Scale Datasets The majority of published research uses proprietary or limited databases. This limits the creation of reliable, broadly applicable models. To enable repeatable AI in formulation, data-sharing programs or federated learning frameworks are desperately needed. Understudied Integration of Multiple Modes A single data type is frequently the focus of existing effort. For instance, molecular descriptor-based solubility prediction and imaging- based QC (such as tablet fault detection) are applied separately. Few studies try to integrate pipelines that include imaging, formulation process, and physicochemical data (e.g., combining stability and dissolution profiles with X-ray pellet surface flaws).

Human–AI Teaming in Dispensing

The usefulness of interpretable Bayesian models for pill verification based on pharmacist preferences was shown by Zheng et al. (2023) (mdpi.com, europepmc.org, pmc.ncbi.nlm.nih.gov). Nevertheless, the majority of AI dispensing systems are completely automated black-boxes that lack the ability to visualize confidence or be overridden by humans. Hybrid-team system designs that include visual explanations, pharmacist intervention choices, and confidence thresholds are required.

Restricted Pilots in the real world and longitudinal evaluations
The majority of research, including studies on automated dispensing cabinets (ADCs), is small-scale or cross-sectional (pmc.ncbi.nlm.nih.gov). It is still uncommon to conduct extensive pilot studies in various pharmacy settings. need long-term studies to assess cost-effectiveness, clinical outcomes (such as adverse events or dose mistakes), operational metrics, and adoption rates [23].

Bias, Equity & Ethical Safeguards

There isn't enough concentrated study on drug dispensing prejudice, despite the fact that bias in AI-trained pharmacy systems—caused by the underrepresentation of minority groups in datasets—has been brought up in larger healthcare contexts (pmc.ncbi.nlm.nih.gov).

There isn't a thorough analysis of how AI dispensing systems could contribute to dose inequalities or prescription mistakes across demographic groups [22].

Standards for Reporting and Regulatory Readiness

Even though healthcare models are currently governed by the TRIPOD-AI, DECIDE- AI, and CONSORT-AI frameworks, AI applications in drug formulation and dispensing are not strictly regulated (en.wikipedia.org). Nevertheless, these essential practices are sometimes overlooked in formulation studies. Transparency, validation, and safety certification need the integration of reporting standards and regulatory alignment.

Infrastructure & Cost Barriers

Studies (e.g., Ethiopian pharmacist surveys) show significant constraints related to infrastructure, funding, and workforce training—especially in resource-limited settings Research to quantify infrastructure needs, economic ROI, and training program effectiveness is needed

Table 1: Summary of Gaps with Proposed Actions

Gap	Implication	Proposed Action
Black-box models dominate	Low clinician trust	IntegrateXAI (SHAP, LIME) (arxiv.org)
Restricted datasets	Poor model generalization	Create shared/formulation federated repositories
Siloed modalities	Incomplete modeling	Pursue multimodal pipelines (physicochemical + imaging)
Automated dispensing lacks user control	Safety risks	Develop human–AI teaming systems
Few real-world studies	Adoption barriers unclear	Launch multi-site, long-duration pilots

Potential demographic bias	Equity concerns	Assess AI fairness across demographic groups
Non-adherence to AI reporting	Regulatory risk	Comply with TRIPOD-AI, CONSORT-AI
Infrastructure constraints	Inaccessible in low- resource areas	Conduct cost-utility and training assessments

The technique described above provides a systematic, moral, mixed-methods approach to assess the present AI applications in medicine formulation and dispensing, ranging from explainability and algorithm development to hybrid system piloting. Interpretability, data transparency, multimodal integration, human-AI cooperation, real-world validation, equitable protections, regulatory harmonization, and capacity-building are all urgently needed, according to the identified gaps in the literature.

Filling up these gaps could hasten the use of AI in the pharmaceutical industry, improving patient safety, dispensing precision, and formulation efficiency. Through algorithm benchmarking, pilot testing, stakeholder involvement, and equity-focused evaluations, the next stage of this research will operationalize these suggestions.

This study traced a unique evolutionary arc by examining how Artificial Intelligence (AI) modifies two fundamental pharmaceutical functions: drug formulation and dispensing. It also compared these advancements with traditional procedures.

From AI Prescriptions to Sumerian Clay Tablets

Around 2600 BC, ancient Mesopotamian healers wrote down medical prescriptions based on herbs, minerals, or animal parts on clay tablets (pubmed.ncbi.nlm.nih.gov, en.wikipedia.org). Hundreds of similar formulations are elaborated in Egyptian manuscripts such as the Ebers Papyrus (c. 1550 BC) (en.wikipedia.org). These formulations—extracted, blended, boiled, or infused—were empirical. Simple dosage forms, such as electuaries, poultices, decoctions, or pressed pills, lacked mechanistic understanding of stability or bioavailability.

Discussion

A significant shift is seen in AI-driven computational pharmaceutics, where computers investigate molecular descriptors, excipient interactions, physicochemical characteristics, and release patterns in silico. These algorithms are refined through the use of generative models, machine learning, deep learning, and genetic algorithms (mdpi.com). In a few of hours, contemporary digital formulator systems can adjust parameters such as compression force and binder composition while synthesizing tiny batches (arxiv.org). It's impressive that a phase that used to take months in the lab may now be finished in less than a day with very little help. Although it reflects broader advancements in pharmaceuticals, this moves from empirical to model-based design marks an unparalleled increase in speed, accuracy, and resource efficiency.

Ancient Quality Control vs. Real-Time AI Monitoring

Traditionally, end-of-production testing based on custom and experience or sensory examination (taste, texture, and appearance) were the only methods of quality control. Despite codifying 482 formulas and dosage forms, medieval pharmacopeias such as the Lorsch Codex (8th century AD) lacked continuous measurement and feedback loops.

To ensure consistency in tablet humidity, porosity, or tensile strength, artificial intelligence (AI) systems now use process analytical technologies (PAT) and real- time sensors to identify anomalies (pubs.rsc.org). Computer vision is used to detect tablet defects, while CFD and discrete event models are used to evaluate the flow of powder in mixers, enabling optimization that was not possible in earlier workshops.

Dispensing: From Apothecary Balances to Automated Precision

System In the past, apothecaries used trumpets and scales to manually measure dosages under the guidance of Arabic pharmacopoeias or monastery compendia. There was little documentation and frequent dosage problems. The 25-chapter drug guides written by apothecaries in 13th-century Cairo lacked systematic dispensing verification [28,29].

The Automated Dispensing Cabinets (ADCs) of today are computerized "pharmacy ATMs," combining unit-dose dispensing, controlled access, clinical decision support, barcode scanning, and precise retrieval (en.wikipedia.org). When compared to manual systems, AI significantly improves accuracy by optimizing storage architecture and pick-sequence through stochastic modeling to decrease retrieval time and error rates (arxiv.org). Comparing Traditional vs. AI Human-in-the-Loop.

Drug making in antiquity was incredibly human-centered, with choices based on custom, oral tradition, apprenticeship, and experience. Explicit computational validation and records were not possible. Artificial intelligence has brought back human involvement constructively. Systems like those at Singapore General Hospital incorporate pharmacist oversight of automated outputs; 75% fewer dispensing errors and 60% faster processing were documented post-AI rollout. Human-AI cooperation within ADCs now allows overrides when confidence scores fall below thresholds —a critical duality of human wisdom and algorithmic precision [30-32].

Knowledge Sharing: From Manuscripts to Open Data

Early formulations, which were frequently preserved and passed down within monastery or cultural limits, survived through centuries-old texts such as the De Materia Medica (1st century AD) and medieval compendia (en.wikipedia.org). Although standardization increased, there was no worldwide, dynamic knowledge ecosystem.

Real-time sharing of pooled data is made possible by modern systems, such as open- source neural model libraries that support drug formulations, federated learning consortia, and generative chemistry frameworks. In only a few seconds, clinical decision support systems may cross-reference patient EHRs, genetic data, and interaction databases—an innovation that was unimaginable in the past [33].

Drug Safety: Transitioning from Culture-Based to Evidence-Based Without established toxicity measurements, toxicity and efficacy were formerly assessed by observation—opium easing pain, Cinchona bark healing malaria, etc.

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Table 2: showing the Ancient Era Shortcoming and AI Innovation

Ancient Era Shortcoming	AI Innovation	Remaining Challenge
Lack of dosage standardization	AI ensures precision unit-dose dispensing	AI bias, data privacy, and regulation (ncbi.nlm.nih.gov, mdpi.com)
Reliance on oral/written wisdom	AI provides mechanistic insights and real-time monitoring	Explainability & human oversight
Manual compounding, laborious	Automation via robotics and ADDS	Infrastructure gaps in low-resource regions
Post-hoc quality inspection	PAT and predictive QC	Integrated multimodal data systems

Conclusion and Recommendation Final Reflections

AI has a revolutionary impact on medicine formulation and distribution, but it is based on centuries of human skill, from medieval apothecaries to Mesopotamian scribes. Unprecedented speed, accuracy, and personalization are made possible by AI, but it also brings back important lessons about human judgment and the importance of interdisciplinary knowledge. Explainability, regulatory compliance, interdisciplinary cooperation, and a strong data infrastructure serve as the foundation for responsible adoption, which can guarantee that AI complements human expertise rather than replaces it [36,37].

AI in pharmacy is an example of a continuum that honors empirical roots while providing customized medicines, safer dispensing, and smarter systems by linking ancient tradition and cutting-edge technology.

As we build on this vast heritage, we must ensure that technology amplifies—not eclipses—the human elements central to care, ethics, and medical wisdom.

Conflict of Interest

The authors declare no conflict of interest.

Authors' Declaration

The authors hereby declare that the work presented in this article is original and that any liability for claims relating to the content of this article will be borne by them.

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