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Editorial

Artificial Intelligence and Decision Making in Clinical Pharmacy

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The incorporation of Artificial Intelligence (AI) into pharmaceutical practice represents one of the most significant transformations in contemporary healthcare. In the health sector, and more specifically in hospital pharmacy, its applications are shaping a new model of operations and patient care, redefining the boundaries of efficiency, safety, and personalization. While discussions about AI often evoke images of robots replacing humans, the emerging reality is one of symbiosis, in which technology amplifies the strategic and clinical capabilities of pharmacists, enhancing safety and efficiency throughout the medication-use process.[1] In this context, the increasing complexity of drug therapies, coupled with the volume and fragmentation of clinical information, poses challenges to pharmacists. AI functions as a tool for cognitive amplification, capable of revealing patterns and anomalies that might otherwise go unnoticed in daily clinical practice. Clinical pharmacy, focused on safety and individualized therapy, finds in AI an ally to improve the accuracy and efficiency of decision-making.

One of the central challenges in pharmaceutical clinical practice is the recognition of prescriptions that deviate from the usual behavior of a given service. Natural variability between institutions—due to therapeutic protocols, epidemiological profiles, and drug availability—makes predictive models based solely on external databases or generic parameters ineffective. In this scenario, the DDC-Outlier (Density-Distance-Centrality Outlier) algorithm[2] emerges as an innovative solution. This unsupervised model analyzes the prescription history of each hospital, learning its internal regularities and identifying deviation patterns. By relying on local reality, the DDC-Outlier accounts for the specificities of clinical practice and avoids the application of artificial criteria that could generate irrelevant alerts.

The principle of the algorithm is simple yet powerful: it identifies prescribed items whose occurrence statistically deviates from the expected behavior within that hospital context. These anomalies, when flagged to the pharmacist, serve as points of attention, guiding a qualified review of the prescription. The tool does not determine errors nor propose automatic substitutions—it highlights what is unusual. This intelligent surveillance strategy reinforces the pharmacist's role as a critical decision-maker and reduces the risk that a potentially unsafe or inappropriate prescription goes unnoticed amid the large volume of clinical data processed daily.

Another significant advancement in supporting pharmaceutical decision-making is the use of Named Entity Recognition (NER) algorithms applied to clinical texts.[2,3] When trained by healthcare professionals, these models can automatically identify relevant information in medical notes, nursing reports, or pharmacy records, such as dialysis data, type of venous access, allergies, and patient weight and height. The result is an automated reading of clinical documents that preserves context without requiring manual review of each record. Automating this process allows pharmacists to focus on elements with the greatest clinical impact, saving time and reducing the risk of omitting critical information.

The accuracy of these models strongly depends on the quality of training and data curation. Generic language models tend to have limited performance when applied to the clinical domain because they do not capture the specific terminology and implicit contexts of electronic health records. For this reason, the active involvement of pharmacists and other healthcare professionals in training algorithms is essential. This collaboration ensures that the extracted entities and identified patterns reflect real-world practice and align with patient safety standards.

A tool incorporating these technologies has been developed by the Health Artificial Intelligence Institute (also known as NoHarm). This platform not only enhances the quality of assessment and operational efficiency but also enables the prioritization of the most critical patients through a global score. This score integrates multiple components: previously unevaluated medications, antimicrobials, high-alert drugs, abnormal laboratory results, an artificial intelligence score that weights unusual prescriptions, and the weighted sum of all generated alerts. In this way, the tool not only identifies potential risks but also guides the prioritization of clinical work, allowing the pharmacist to focus on the most severe cases.

NoHarm platform alerts are built on well-established technical foundations, many of which are independent of AI but essential for clinical decision support. These alerts rely on programmed logic and rules based on pharmacotherapeutic knowledge to identify situations requiring immediate attention. Key examples include dosage adjustment alerts based on renal function, alerts for contraindications or the need for risk-benefit assessment in patients with thrombocytopenia, and medications not recommended for administration via feeding tube.

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Additionally, the platform flags potentially inappropriate medications for older adults according to updated criteria and alerts for allergies and cross-reactivity, which cross-reference electronic health record data with the chemical structures of prescribed drugs.

The platform also monitors maximum doses, both per individual item and cumulative duplicates, and issues alerts for excessive treatment duration, duplicate medications, and duplicate therapies. Other rules address severe drug interactions, Y-site incompatibility, and the risk of acute kidney injury (AKI) associated with vancomycin use when the dose-to-weight-to-glomerular filtration rate (GFR) ratio exceeds safe parameters.[5]

These programmed alerts demonstrate that clinical decision support does not rely solely on artificial intelligence. In this context, AI acts as a complement to the existing technological framework, enhancing its capacity for contextualization and prioritization. While structured rules ensure precision and predictability, unsupervised learning models and natural language processing allow continuous adaptation to the reality of each hospital. The result is a hybrid system that combines deterministic logic with adaptive learning, providing greater robustness and sensitivity to the clinical assessment process.

The evolution of Large Language Models (LLMs) further reinforces this complementary potential. These models, increasingly capable of explaining the sources of information used in their inferences, contribute to greater transparency and auditability of automated decisions. Although the risk of "hallucination" remains, the trend is that the integration of LLMs, specific algorithms such as DDC-Outlier, and traditional clinical rule modules will achieve a balance between innovation and safety.[6]

NoHarm's experience demonstrates that AI, when responsibly and supervisedly incorporated, can expand the scope and quality of clinical pharmacy. It enhances human work, making critical information more visible and reducing the likelihood of errors resulting from data overload. Artificial intelligence, therefore, does not replace the pharmacist: it empowers them, offering new lenses to view care and strengthening the central commitment of the profession—the safe and rational use of medications.

About the authors

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