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EDITORIAL ARTICLE

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Role of Automation, Natural Language Processing, Artificial Intelligence, and Machine Learning in hospital settings to identify and prevent Adverse Drug Reactions

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ABSTRACT

Patient Safety is at the center of all pharmacovigilance activities. As several covariates can impact the safety of a medicinal product in patients, a large amount of data is required for an accurate assessment of the safety and therefore, the benefit-risk balance of a medicinal product. Natural language processing, Artificial Intelligence, and Machine Learning are being popularly used to facilitate various pharmacovigilance activities in the Pharma industry. Artificial Intelligence and Machine learning if properly used in hospital settings can also facilitate the identification of adverse events from hospital records and discharge summaries and prescription errors, thus, alerting treating physicians regarding the same. However, the potential of using these techniques needs to be fully explored in hospital settings to facilitate the collection and evaluation of safety data.

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Introduction

Pharmacovigilance (PV) essentially involves the collection, processing, and evaluation of large numbers of case reports for the identification of new adverse reactions (ADRs) i.e., signal detection followed by signal confirmation and implementation of appropriate Risk Management Plans (RMPs). It is important to note that these case reports are not only used to identify adverse reactions, the scope of signal detection also includes identifying drug-drug interactions, food drug interactions, pharmacokinetics in special populations, for example, geriatric and pediatric populations, adverse reactions in patients with hepatic and/ or renal failure and the effects of drugs in pregnant or lactating women. A study of these case reports can also help in identifying patients who are at greater risk due to genetic factors, comorbidities, or personal lifestyle factors like smoking, alcohol consumption, or drug abuse. Knowledge regarding the adverse reaction of drugs including considerations for special situations along with RMPs is essential to ensure patient safety. Therefore, all Pharmacovigilance activities at the level of various stakeholders, i.e., the pharmaceutical industry, healthcare professionals, regulators, and pharmacovigilance centers are planned and conducted considering this central theme of pharmacovigilance.

Use of Information Technology in Pharmacovigilance

Effective pharmacovigilance systems are the ones that are based on large data. This requirement of processing large data makes pharmacovigilance function an important user of technology demanding various advancements in information technology (IT). IT systems have helped pharmacovigilance by harmonization of data for example

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E2B reports, coding of adverse events and drugs, implementation of 21 CFR Part 11, data privacy, etc. (Bate A., 2022).

Automation, Artificial intelligence, Machine learning, and Natural Language Processing

Automation includes predetermined decision criteria guiding the subprocesses. Artificial Intelligence (AI) using Machine Learning (ML) is an advancement over automation through which computers are programmed to learn. Computers can be programmed to learn including deep structural learning using neural networks that can mimic human cognitive learning, which is popularly known as ML and AI. An important component of AI & ML is Natural Language Processing (NLP) which involves the development of programs through which computers can recognize texts and voices like humans and respond accordingly.

IT Advancements in the Pharma industry

The Pharma industry has taken a lead in the use of IT systems and today, pharmacovigilance departments of pharma companies have essentially become paperless. Pharmacovigilance departments are also effectively integrating automation, AI, ML, and NLP in various pharmacovigilance processes.

IT Advancements in Hospital settings

At the level of the hospitals, the role of computerized systems in maintaining electronic medical records is well established. Computerized systems are also used for large-scale redaction of data to remove personal information and thus, facilitating the use of data for retrospective and prospective studies. Medical science is rapidly advancing and leads to frequent updates in the applicable information related to therapies for example first line of treatment, new ADRs, factors leading to increased risks, new drug-drug interactions (DDIs), etc. New information is used to update specific hospital or specialty procedures, for example, treatment protocols, policy on the purchase of drugs and hospital equipment, etc. Thus, it is very important to disseminate new information to the right stakeholders for relevant actions. Automation can also help in ensuring that critical information promptly reaches all stakeholders (De Vries, 2022).

Role of Automation, NLP, AI, and ML in Hospital Settings

Nowadays, automation is used in hospital settings to alert healthcare professionals (HCPs) regarding potential DDIs, increased risk due to comorbidities, dose selection, and the presence of patient conditions classified as contraindications. These HCPs include prescribing doctors, dispensing pharmacists, and nurses who administer the drugs. Automation can be also used to effectively disseminate new safety information.

In hospital settings, the use of NLP will be particularly important to read prescriptions (Luo et al., 2017). Multiple covariates need to be taken into account during patient management and the development of a decision tree is extremely helpful in emergency settings. However, on a daily basis, while selecting a treatment for a patient, doctors consider several factors, for example, stage of the disease, recent progression, comorbidities, age of the patient (adult, child, or elderly), risk factors, concomitant medications, family history, genetic predisposition, liver and kidney functions, pregnancy/ planning pregnancy, personal preferences for drugs, individual factors like smoking, alcohol, drug abuse; feasibility of regular follow-ups, home care, cost of the treatment and health insurance. While a decision tree can help, oversimplifying the selection of a particular treatment in the form of a decision tree. i.e., developing a rule-based model for optimal selection of treatment may not be justifiable. Thus, in such settings, it is recommended to implement an efficient ML and AI system which can familiarize itself with choices made by the prescribers and quickly develop algorithms.

Like HCPs need to be regularly updated with the latest developments in therapy and knowledge regarding drugs, computers also need to be consistently fed the latest data so that ML and AI remain relevant.

Preventable ADRs

Various studies have concluded that many ADRs are preventable. The percentage of preventable ADRs reported in these studies varies from 22 % to 70 %, most of them concluding around 50 %. Thus, it is a critical area that requires attention to ensure the safety of the patients, optimal use of resources, and increased cost efficiency of treatments.

As reporting of ADRs remains poor, ML has been used to identify ADRs from discharge summaries (Tan et al., 2022). ML is also utilized to test hypotheses and develop appropriate solutions. For example, if the elderly with new prescriptions of Central Nervous System (CNS) drugs are more prone to overdose/ poisoning, then these patients as well as their caretakers should be advised to take appropriate precautions, including restricting the number of tablets to be dispensed. It is important to understand here that while dispensing for a longer duration will save the elderly trouble to frequently visit hospitals, it may also make them more susceptible to overdose, therefore, an optimal, balanced approach can be recommended considering various other local factors and discussions with the caretaker (Zhao et al., 2022).

Role of Automation, NLP, AI, and ML in Hospital Settings to Prevent ADRs

ML can be used to identify ADRs retrospectively, through the use of hospital records. It is also important to identify various factors associated with increased susceptibility to various ADRs, for example, age, gender, comorbidities, and polypharmacy with the help of multivariate analysis. While automation can play an important role in preventing prescription errors and ADRs of overdose, drug-drug interactions by alerting healthcare professionals, adequate algorithms can also be developed to facilitate early identification of ADRs, which in turn can be helpful by taking early action to control the harm to the patients (Lee et al., 2021). For therapies involving complex decision-making, AI and ML can play an important role.

Conclusion

There is a need and enormous potential to utilize ML in hospital settings to make more effective use of IT and reduce excessive burden and pressure on prescribers and other healthcare professionals. Thus, there is a need to increase focus on increasing pharmacovigilance activities through AI and ML. Optimal, appropriate, and adequate implementation of AI and ML requires a team of pharmacovigilance experts with basic knowledge of AI and ML and a team of IT experts with a basic understanding of pharmacovigilance. We look forward to seeing more efforts to integrate AI and ML in hospital settings to reduce the number of preventable ADRs.

Conflict of interest

The authors declared that there is no conflict of interest.

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