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Review Paper

Role of Artificial Intelligence in Hospital and Clinical Pharmacy: A Review

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ABSTRACT

By improving the precision, effectiveness, and security of healthcare delivery, artificial intelligence (AI) is quickly changing hospital and clinical pharmacy procedures. The integration of AI technologies in pharmacy and hospital settings, including machine learning, deep learning, natural language processing, and clinical decision support systems, is highlighted in this review. AI is essential for evidence-based treatment, dose optimization, drug interaction detection, and medication error reduction. Pharmacogenomics and patient-specific medication therapy are two more ways it supports personalized medicine. Additionally, patient counseling, monitoring, and clinical decision-making are enhanced by AI-driven tools like chatbots, electronic health records, and predictive analytics. Notwithstanding its many benefits—such as enhanced patient safety, decreased workload, and improved accuracy—problems like data privacy, high implementation costs, a lack of training, and ethical dilemmas still exist. Future prospects are also covered in the review, including smart clinical pharmacy systems, AI-integrated hospitals, and the development of AI in India. All things considered, AI has the potential to completely transform clinical pharmacy by reorienting pharmacists' roles toward more patient-centered and data-driven care...

INTRODUCTION

A common definition of intelligence is the capacity to gather information in order to address challenging issues. Intelligent machines will soon surpass human capabilities in numerous domains. The study of intelligent machines and software that are capable of reasoning, learning, gathering information, communicating, manipulating, and perceiving objects is known as artificial intelligence[1].

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Nearly every industry has innovated over time and developed a number of concepts that could facilitate their work. While some businesses have integrated AI into their workplaces, hospital pharmacies lack innovation, particularly in this area. We continue to discover that the majority of tasks are completed by hand, which is prone to numerous human errors and can result in negative consequences and employee burnout[2].

By increasing the precision and effectiveness of clinical decision-making, reducing diagnostic errors, and facilitating customized treatment plans, artificial intelligence (AI) is revolutionizing the medical field. Healthcare professionals can analyze vast amounts of patient data, identify intricate patterns, and make evidence-based predictions thanks to AI-powered technologies like machine learning, deep learning, and natural language processing. Among the specialties that gain the most from these capabilities are radiology, pathology, cardiology, and cancer[3,4,5].

Artificial intelligence is transforming healthcare operations beyond diagnosis and treatment planning, including robotic-assisted surgeries, virtual patient consultations, and electronic health record administration [6]. AI-driven chatbots and virtual assistants provide round-the-clock patient assistance, answering medical queries and helping with medication compliance [7]. AI in robotic surgery increases accuracy while lowering the risk of complications, leading to quicker recovery times and better patient outcomes [8].

A. Types of AI Used in Clinical Pharmacy :

1. Machine Learning & Deep Learning :

A subfield of artificial intelligence called "machine learning" employs algorithms to enable robots to learn from data and improve over time [9]. Certain tasks in robotics, like grasping, object recognition, and path planning, can be programmed into robots. Deep learning, a subset of machine learning (ML), uses artificial neural networks to enable computers to learn from enormous amounts of data [10]. In robotics, DL has proven especially helpful for tasks like object detection, natural language processing, and image and speech recognition. When combined, these technologies have made it possible to create robots that can carry out a variety of tasks, from straightforward pick-and-place operations to intricate manipulation and unstructured environment navigation . Robots can learn from their experiences and gradually improve their performance thanks to machine learning. Certain issues, like image and speech recognition, that are challenging to resolve with conventional machine learning methods are addressed by deep learning. These technologies can be combined to create sophisticated robotics systems that can carry out difficult tasks that were previously unthinkable[11].

Here are a few instances of their applications in various robotic systems:

- **Object Detection and Recognition:** Deep learning has made it possible to perform important robotics tasks like object detection and recognition. Robots are able to accurately identify and classify objects in their surroundings by training neural networks with vast amounts of labeled data [12].
- **Predictive maintenance** is a maintenance strategy that makes use of AI and ML to identify possible problems before they arise. Predictive maintenance algorithms can anticipate when a robot's parts might break by evaluating data from sensors and other sources, enabling proactive repairs or replacements [13].
- **Gesture and Speech Recognition:** Another significant use of AI and ML in robotics is gesture and speech recognition. Robots like Pepper, for instance, are helpful in a range of settings, including customer service and

healthcare, because they can identify and react to human speech and gestures [14].

- **Robotic Surgery:** AI and ML are transforming the way operations are carried out in this field. Robotic surgeons can help human surgeons with difficult procedures by utilizing sophisticated algorithms, which lowers the possibility of complications and improves results. AI, ML, and DL are used by surgical robots to help surgeons carry out difficult procedures more precisely and accurately [15].

2. Natural Language Processing (NLP) :

Natural language processing (NLP) has undergone a radical change with the introduction of artificial intelligence (AI), moving from a rule-based system to a more dynamic and adaptable model. The limitations of rule-based algorithms, which were unable to comprehend the subtleties and complexity of human language, significantly limited NLP prior to artificial intelligence [16]. Natural Language Processing (NLP) is a specialized area within AI that focuses on enabling machines to understand, interpret, and generate human language. With the integration of AI, especially deep learning, NLP has become more efficient and versatile, capable of handling a wide range of tasks from translation to sentiment analysis[17]. Applications of NLP include machine translation, question-answering systems, sentiment analysis, and text classification [18]. NLP is both an application and an essential component of AI research since machine learning algorithms, especially deep learning, are frequently used in NLP to analyze and interpret massive natural language datasets [19]. AI plays an essential role in NLP. AI technologies play a major role in the majority of contemporary NLP tasks, including text summarization, sentiment analysis, and document translation.

3. Clinical Decision Support Systems (CDSS):

In many areas of medicine, the combination of clinical decision support systems (CDSS) and artificial intelligence (AI) has become a revolutionary force. By providing clinicians with evidence-based information, these systems aim to improve patient outcomes, optimize treatment selection, and increase diagnostic precision. AI-enabled CDSS has shown promise for initial implementation in primary care settings, streamlining clinical workflow, and improving decision-making ability in low-resource settings [20,26]. The power of large language models in context-dependent, real-time decision support in the acute setting is made possible by the expanding use of AI in emergency medicine [25].

However, for adoption to be successful, both the technological and human factors—such as usability, reliability, and interpretability—that impact clinician interaction with these systems must be taken into account [21]. With a greater focus on health technology evaluation in terms of safety, cost-effectiveness, and ethics, AI technologies in oncology, such as breast cancer diagnosis, demonstrate the capabilities of machine learning in subspecialty diagnosis [22]. Furthermore, the expanding application of AI in emergency medicine makes use of large language models for context-dependent, real-time decision support in an acute setting [25].

The need for context-adjusted strategies is suggested by the heterogeneity in CDSS adoption on a global scale. Chinese implementation strategies, for instance, have different applications and problems, such as infrastructure readiness and integration into current care pathways [24]. In addition to functionality, the ethical aspect of AI in healthcare has drawn increased attention, especially in terms of enabling compassionate care and guaranteeing that technological developments align with patient-centered values [23].

B. Applications of AI in Hospital Pharmacy :

1.Medication Error Reduction:

Despite being preventable in many cases, adverse drug events (ADEs) continue to be a significant concern for hospitalized patients, contributing to morbidity, mortality, and higher healthcare costs. By producing medication alerts based on electronic health records (EHRs), clinical decision support systems (CDSSs) are frequently used to lower adverse drug events (ADEs). These notifications help medical practitioners spot problems like allergies, medication interactions, and dosage mistakes.However, traditional CDSSs frequently generate a large number of low-relevance alerts, which can jeopardize patient safety by causing alert fatigue and frequent overrides. Inadequate consideration of contextual and patient-specific factors is the main cause of this limitation.A number of optimization techniques, such as alert inactivation, severity reclassification, and contextual data incorporation, have been put forth to address this. Artificial intelligence (AI) methods, including machine learning, deep learning, and natural language processing, have recently demonstrated promise for improving CDSS performance by enabling more precise, patient-specific, and clinically relevant alerts.Despite these developments, there is still a lack of research on the use of AI to optimize medication alerts for hospitalized patients [27].

2.Clinical Decision Support Systems (CDSS):

A clinical decision support system (CDSS) seeks to improve healthcare delivery by improving medical decisions with targeted clinical knowledge, patient data, and other health information. Software designed to directly assist clinical decision-making makes up a traditional CDSS. It accomplishes this by comparing a patient's attributes to an electronic clinical knowledge base and providing the clinician with patient-specific recommendations or evaluations. These days, CDSSs are primarily used at the point of care, where the clinician integrates the CDSS's data or recommendations with their own expertise. However, an increasing number of CDSS are being developed that make use of observations and data that would not otherwise be accessible or understandable to humans[28]. Nevertheless, CDSSs have received less attention in the context of mental health than physical health. Few studies have examined the experiences and/or opinions of mental health professionals regarding these systems, even though they are the main users of mental health CDSSs. Moreover, we are not aware of any reviews that concentrate on this particular subject. We carried out a scoping review to map the state of the art in research looking at CDSSs from the viewpoints of mental health professionals in order to close this gap[29].

- **Drug Interaction Checking :**

Drug interactions are defined as interactions between a medication and another substance that have the potential to increase or decrease the medication's efficacy or exacerbate its adverse effects. Numerous procedures could result in interactions between drugs. The pharmacokinetics of the medication may be altered as a result of these procedures, the distribution, metabolism, excretion, and absorption of the medication. Additionally, drug interactions may result from the pharmacodynamic properties of the medication, such as the administration of an agonist and a receptor antagonist collectively for the same receptor. The expected efficacy of a medication may be drastically changed when taken with other drugs, specific foods, or when it interacts with bacteria in the gut. Understanding interactions between drugs including interactions between drugs (DDI). Drug development and post-marketing procedures can be enhanced by anticipating drug interactions (DDIs). surveillance while reducing the possibility of negative reactions. Clinical trials are expensive, time-consuming, and impractical when handling massive volumes of data and the boundaries of experimental conditions. To accelerate The researchers use a variety of computational methods to expedite the prediction process. The present computational Five broad categories can be used to classify DDI prediction techniques: deep learning, network analysis, literature extraction, matrix factorization, and similarity analysis [30]. Drug-drug interactions, or DDIs, are a serious threat to patient safety. By offering digital services to patients and healthcare providers, eHealth solutions have the potential to solve this issue and generally enhance medication management. There is a wealth of professional research on clinical decision support systems (CDSS), which are frequently used to notify doctors or pharmacists about DDIs. Patients frequently ask for information about DDIs, but little is known about how to offer them comparable assistance [31].

- **Dose Recommendation :**

A "specific dose recommendation" was deemed to meet the inclusion criterion if: (1) a specific dose recommendation was given (in [%] or in the corresponding unit, e.g., [mg]); (2) a precise indication of the prolongation or shortening of a dose interval was given (in hours [h] or alternating schemes, e.g., "every other day"); (3) it was stated that no dose adjustment was required; (4) it was obviously necessary to avoid; or (5) an alternative active substance was indicated that should be preferred. Furthermore, the requirements had to be met for each of the three classes if a publication provided different dose recommendations for each Child-Pugh class. Both statements were examined independently for specificity if a publication contained two statements within a recommendation (for example, on dose adjustment and interval extension) or if recommendations were given for various active ingredient formulations or administration routes. The following situations were not classified as specific: (1) general recommendations of therapeutic drug monitoring if no suitable starting dose was given; (2) unspecific recommendations like "precaution" or "start as low as possible" because they could be interpreted in different ways; and (3) whenever authors were unable to provide recommendations due to a lack of data [32].

- **Evidence based Therapy:**

Psychotherapy is being impacted more and more by the demand for evidence-based practice. The American Psychological Association (APA) made significant early efforts to create a specific list of treatments that have been shown to be effective. The American Psychological Association (APA) has recently started formal efforts to define and establish more thorough evidence-based practices and treatment guidelines that are unique to psychology. However, in the years to come, both psychotherapy researchers and evidence-based practitioners will face formidable obstacles. Even though there is evidence that psychotherapy should be the primary treatment, clinical psychology is already lagging behind established psychiatric treatment guidelines that occasionally favor medication over psychotherapy [33]. Evidence-based psychotherapies have benefits for patients, clinical teams, and practitioners. It has been argued that practice must be guided by pertinent data in order to be ethical. Instead of depending only on their own judgment, healthcare professionals employ research-driven evidence by integrating research into clinical practice. Empirical evidence lessens the opinion-based bias of remembering only "successes." When used properly, EBP can support clinical judgment. Research integration invariably encourages the creation of databases, guidelines, and other clinical tools that can support clinicians in making important treatment decisions, especially in community-based settings. In order to achieve the best results, evidence-based psychotherapy incorporates both local and scientific evidence, such as patient diagnostic data; situational information, such as time and cost constraints; and the provider's judgment and experience [34].

3. Personalized Medicine:

The idea of "personalized" medicine is very popular. The foundation of personalized medicine is the idea that since each person has distinct and subtle traits at the molecular, physiological, environmental exposure, and behavioral levels, they may require interventions for diseases that are specific to these traits. The use of cutting-edge technologies like DNA sequencing, proteomics, imaging protocols, and wireless health monitoring devices, which have shown significant inter-individual variation in disease processes, has partially validated this belief. In this review, we take into account the reasons behind personalized medicine, its historical precedents, the new technologies that are making it possible, some recent experiences, including both successes and failures, methods for screening and implementing personalized medications, and future directions, such as possible treatments for people with sterility and infertility problems. We also take into account the present constraints on personalized medicine. In the end, we contend that because some aspects of personalized medicine are grounded in biological realities, personalized medicine practices in some contexts are probably inevitable, particularly as pertinent assays and deployment strategies become more effective and economical [35].

- **Patient-specific drug Therapy :**

The core of personalized medicine in the pharmacy industry is its ability to minimize side effects, improve medication efficacy, and maximize treatment results. Because they have greater target specificity and biological activity than small-molecule chemical drugs, protein drugs are currently the mainstay in the field of personalized drug therapy. This makes them effective in controlling disease-related biological processes and holds great promise for the development of personalized drugs. Nowadays, patient-specific protein data is used to design and develop protein drugs for particular protein targets. But thanks to the quick development of mass spectrometry and two-dimensional gel electrophoresis, it is now widely acknowledged that a canonical protein actually consists of several proteoforms and that the variations in these proteoforms will lead to different drug responses. Different proteoforms can have quite different effects, and this can even change a drug's intended benefit, making it potentially harmful rather than life-saving [36].

- **Pharmacogenomics Integration :**

In contrast to the traditional approach, pharmacogenomics is a new science based on gene-drug interactions that can be used to discover new drug molecules for current diseases and further design novel, more effective formulations of existing drugs in a shorter amount of time with better utilization of available resources. Pharmacogenomics began as the study of drug response variation and genetic variations in defined populations, such as particular ethnic groups. But as science has progressed, it has evolved into the study of individual genetic variations regardless of ethnicity and other racial differential systems. It is a useful tool for establishing disease-gene, gene-drug, and drug-effect correlations based on the human genome. It is the study of gene polymorphism (genetic variability) that causes variation in drug response. Drugs are created to treat illnesses and improve conditions, but occasionally they don't have the desired therapeutic effect, which causes adverse drug events in some patients. Genetic variability may be the cause of this variation in drug response. Target biomarkers, mechanism biomarkers, outcome biomarkers, toxicity biomarkers, and diagnostic biomarkers are just a few of the disease-drug interaction research processes for which the pharmacogenomic principle can be applied [37].

4. Drug Information & Patient Counseling:

Patient medication counseling regarding side effects, drug usage, medication history, and allergies was reported by both community pharmacists and pharmacy patrons. Although the pharmacists' counseling was of a satisfactory caliber, the customers' counseling was of a subpar caliber. During medication counseling, pharmacists might need to interact with pharmacy patrons more [38]. It is important to consider patient counseling as a part of the entire drug-use process. Pharmacists who counsel patients who are prescribed long-term medications must be aware of the lifestyle impacts of chronic illness, especially the various forms of "work" that these patients must perform. When counseling patients, pharmacists must go beyond the conventional sender-message-receiver communication models and instead take a problem-solving approach that considers the needs and comprehension level of each individual patient. Patients ought to actively participate in choosing their course of treatment. Counseling must be tailored to each patient's stage of change in order to maximize therapeutic outcomes, as patients will be at different stages of making any necessary behavioral changes. Open-ended questions are used in the Indian Health Service (IHS) counseling model to assess patients' understanding of their condition and prescription drugs. This allows the pharmacist to review specific points and fill in any gaps. The IHS model is complemented by the health communication model, which offers methods for improving patient compliance and recall [39].

- **AI chatbots:**

A major development in healthcare is the use of chatbots and virtual health assistants (VHAs) in patient counseling. These technologies offer creative ways to increase patient involvement, increase access to health information, and support chronic illness self-management. Significant obstacles still need to be overcome despite their increasing use, such as guaranteeing the accuracy of artificial intelligence (AI)-driven recommendations, upholding patient confidence, and resolving moral issues like algorithmic bias and data privacy. With an emphasis on user-centered design, this review explores the changing role of chatbots in patient counseling and their effects on patient engagement, adherence, and satisfaction. We examine how various designs affect patient interactions and treatment outcomes by investigating AI-powered, rule-based, and hybrid chatbot models. Case studies demonstrate the potential of chatbots to offer round-the-clock availability, cost effectiveness, and scalability in the areas of mental health support, chronic disease management, and medication adherence. To maximize their implementation, however, issues like data security, emotional intelligence deficiencies, and the requirement for regulatory frameworks must be resolved. In order to enable the safe and efficient use of chatbots in healthcare, this article emphasizes the significance of evidence-based guidelines and continuing research. Future developments that promise to further improve their role in patient counseling include emotionally intelligent AI, wearable device integration, and blockchain for data security. In order to build trust and enhance healthcare outcomes, this review ultimately promotes a cooperative strategy that places a high priority on patient-centered design, regulatory transparency, and ethical AI deployment [40].

5. Electronic Health Records (EHR) Integration :

- **Data Analysis & Patient History Tracking :**

Clinically relevant information gathered by patients outside of the conventional care setting is known as patient-generated health data (PGHD). The use of PGHD in clinical settings has become crucial. In order to ascertain the degree of and characterize the features of PGHD integration into electronic health records (EHRs), this study examined the available data [41]. Health systems are becoming more and more reliant on EHR capabilities, offerings, and innovations to better capture patient data as a result of the adoption of electronic health records (EHRs) and legislation on meaningful use in recent decades. Integration of wearable health technology with EHRs is a new capability provided by health systems. Wearables have the potential to revolutionize patient care, but providers' adoption of wearables is hampered by problems like patient privacy concerns, system interoperability, and patient data overload [42]. Patient-generated health data (PGHD), which can support the delivery of individualized care, may be included in patients' medical records. Healthcare practitioners who have access to these data may be able to obtain more information that will help them make decisions and offer more assistance. This review attempts to offer evidence on PGHD integration with electronic health records (EHR), models and standards for PGHD exchange with EHR, and PGHD-EHR policy design and development in light of the various sources of PGHD. Governance and socio-technical aspects of PGHD management are also covered in the review [43].

6. Antimicrobial Stewardship:

A comprehensive strategy to stop the development of antimicrobial resistance must include antimicrobial stewardship. Choosing the right medication and maximizing its dosage and duration to treat an infection while reducing toxicity and creating an environment that encourages the emergence of resistant bacterial strains are key components of good antimicrobial stewardship. Research over the years shows that up to 50% of cases in the US involve the unnecessary or inappropriate use of antibiotics, which puts undue pressure on the selection of resistant species. A premium has been placed on preserving the efficacy of currently available agents because the pharmaceutical industry's pipeline for new antibiotics has been reduced recently, and it may take more than ten years before significant new antibiotics to treat some resistant bacteria reach the market [44].

- **AI in Selecting Appropriate Antibiotics:**

Antibiotic resistance (ABR) is a result of antibiotic use. ABR has been predicted and controlled using a variety of techniques. Artificial intelligence (AI) has been investigated in recent years to enhance the prescription of antibiotics (AB), thereby controlling and lowering ABR. Antibiotic stewardship programs (ASPs), which are defined as a collection of interventions that encourage the responsible use of antibiotics, and clinical decision support systems (CDSSs), which provide clinicians with patient-related recommendations and assessments to aid in their decision-making, are two examples of various approaches that have been used to improve antibiotic prescribing. These techniques aim to alter behavior. Furthermore, ASPs typically have a short-term impact and require ongoing work [45].

- **Resistance Prediction:**

A global health crisis has been brought about by the emergence and spread of antimicrobial resistance (AMR) mechanisms in bacterial pathogens as well as the decline in the number of effective antibiotics. Clinical decision-making and reaction time could be enhanced by being able to determine the genetic mechanisms of AMR and forecast the resistance phenotypes of bacterial pathogens before they are cultured. For a number of years, PATRIC has been gathering bacterial genomes with AMR metadata. We have updated the PATRIC FTP server to allow access to genomes binned by their AMR phenotypes, along with metadata such as minimum inhibitory concentrations, to facilitate phenotype prediction and the identification of genomic regions associated with AMR. We developed AdaBoost (adaptive boosting) machine learning classifiers specifically to detect carbapenem resistance in Acinetobacter baumannii using this infrastructure. Accuracy ranges from 88 to 99% for methicillin resistance in Staphylococcus aureus and beta-lactam and co-trimoxazole resistance in Streptococcus pneumoniae. Additionally, we achieved accuracy ranging from 71 to 88% for isoniazid, kanamycin, ofloxacin, rifampicin, and streptomycin resistance in Mycobacterium tuberculosis. An initial framework for species-specific AMR phenotype and genomic feature prediction in the RAST and PATRIC annotation services has been developed using this collection of classifiers [46].

7. Adverse Drug Reaction (ADR) Monitoring: Adverse drug reactions (ADRs) are considered as one among the leading causes of morbidity and mortality. Around 10% of hospital admissions are estimated to be due to ADRs and about 5-20% of hospitalized patients experience a serious ADR. Reporting of ADRs has become an important component of monitoring and evaluation activities performed in hospitals4. Such ADR reporting programs encourage surveillance for ADRs, promote the reporting of ADRs and stimulate the education of health professionals regarding potential ADRs [47]. The monitoring of adverse drug reactions caused by medications used to treat illnesses is a crucial part of pharmacovigilance. When medications are administered, adverse drug reactions (ADRs) result in negative or unwanted effects on the body. According to reports, the number of patients dying each year as a result of adverse drug reactions has increased by up to 2.6 times. Additionally, hospitalization rates are rising as a result of medication side effects. As a result, resolving the related issue of ADRs becomes difficult for doctors, healthcare providers, the WHO, and the pharmaceutical industry. It is important to investigate a novel drug's dependability during clinical trials. In this review, we recorded the information needed to identify adverse drug reactions (ADRs) in patients as well as reported banned medications [48]. Adverse drug reactions (ADRs) are one of the most significant problems in the modern healthcare system, contributing significantly to patient morbidity and mortality as well as consuming a large portion of healthcare costs worldwide. According to research, ADRs account for 5–10% of all hospital admissions; rates in older populations are even higher [47]. The World Health Organization (WHO) defines adverse drug reactions (ADRs) as noxious, unintentional drug reactions that occur at doses commonly used in humans to prevent, diagnose, treat, or modify physiologic activity [48]. Rigorous pre-marketing clinical trials have not made it possible to detect many adverse drug reactions (ADRs), despite the fact that ADRs are frequently discovered after medications are widely used in clinical settings [49].

C. Role of AI in Clinical Pharmacist Activities:

1. **Medication therapy management (MTM) :**

Medication therapy management plays a crucial role in optimizing drug therapy outcomes, ensuring patient safety, and reducing adverse drug reactions. Traditional MTM approaches rely heavily on manual intervention, clinical expertise, and pharmacist-led consultations. However, these conventional methods face challenges such as human error, inefficiencies in drug regimen monitoring, and difficulties in personalizing treatments for diverse patient populations.Artificial intelligence and digital health technologies have emerged as transformative tools in healthcare, offering innovative solutions to enhance medication therapy management.Adverse drug reactions (ADRs), drug-drug interactions, polypharmacy, and improper medication use are among the medication-related issues that older adults are most susceptible to. Poor adherence to evidence-based recommendations, communication breakdowns, a lack of deprescribing procedures, and a lack of knowledge about medication use are frequently the causes of these problems. In order to guarantee safe and sensible drug use while averting possible adverse drug reactions, coordinated medication therapy management (MTM) and evidence-based prescribing are crucial.[50-54].

2. Clinical Interventions :

Clinical studies are used by researchers to provide evidence to healthcare decision-makers so they can evaluate and prioritize various interventions. These decision-makers include payers, regulators, and other healthcare executives; each has different levels of authority and interest, but they all have crucial decisions to make. 1. The quality of these decisions is determined by the four essential stages of evidence generation and evaluation: study design, study conduct, study reporting, and study appraisal. The clinical trials industry is confronted with a complex crisis marked by rising expenses, protracted timelines, and systemic inefficiencies that seriously compromise its main objective of providing patients with life-saving treatments. Modern Phase III trials take six to seven years to complete and require an average investment of $19 million [55]. Patient recruitment is the most important issue; 80% of trials have major delays because of enrollment issues, and 7% of research sites are unable to find a single participant [56]. In addition to significantly raising costs and delaying patient access to potentially life-saving treatments, this recruitment failure lengthens trial timelines by an average of 6–8 months. Furthermore, conventional data collection techniques have a high error rate because they mainly rely on manual procedures. Research shows that up to 50% of clinical trial data have errors or inconsistencies, necessitating lengthy cleaning procedures that further postpone the completion of the study [57].

3. Monitoring Patient Outcomes:

Artificial Intelligence (AI) is significantly improving the monitoring of patient outcomes by enabling continuous and real-time assessment of health data. AI systems integrate information from wearable devices, sensors, and electronic health records to track vital signs and detect early signs of clinical deterioration. Advanced algorithms such as machine learning analyze large datasets to identify patterns and predict potential health risks, supporting timely medical interventions and improving clinical decision-making[58].

AI-based monitoring also allows remote and personalized patient care, especially for individuals with chronic diseases and elderly populations. These systems reduce human error, enhance accuracy, and enable early warning of complications, leading to better treatment outcomes and reduced hospital admissions. However, challenges such as data privacy, algorithm bias, and the need for proper validation must be addressed to ensure safe and effective use of AI in healthcare[59].

D. Advantages of AI:

1. **Improved Patient Safety:**

Next big thing in health technology is artificial intelligence (AI), which has the potential to significantly increase patient safety. Sepsis detection and prediction, pressure ulcers, postpartum hemorrhage, adverse drug events, and patient decompensation are a few examples [60,61]. However, AI in clinical settings may cause harm to patients if it is not properly designed, developed, implemented, and used. For instance, a popular AI system designed to identify sepsis patients only identified 7% of 2552 sepsis patients, delaying the administration of antibiotics and failing to identify 1709 sepsis patients that the hospital found using other methods [62]. One useful tool that could be utilized to raise the standard of care is artificial intelligence (AI). Healthcare-associated infections, adverse drug reactions, venous thromboembolism, surgical complications, pressure ulcers, falls, decompensation, and diagnostic errors are among the most common adverse events in healthcare. This scoping review's goals were to compile pertinent research and assess how AI might enhance patient safety in these eight harm domains. MEDLINE was queried using a structured search to find pertinent articles. Studies that discussed the use of AI for early detection, prevention, or prediction of adverse events in each of the harm domains were found through the scoping review. To estimate the likelihood that AI will improve safety, the AI literature was narratively synthesized for each domain, and the results were taken into account in relation to incidence, cost, and preventability [63].

2. **Faster Decision-Making :**

Artificial intelligence significantly enhances decision-making by speeding up and improving the quality of decisions. Massive volumes of data can be swiftly processed by AI systems, which can also identify patterns and generate data-driven insights that reduce biases and human error while increasing decision accuracy. Additionally, AI enables the automation of repetitive tasks, which enhances and expedites decision-making while freeing up human resources for more complicated choices. It also ensures decision consistency by employing the same models and guidelines consistently. Additionally, AI makes predictive analytics possible, allowing decision-makers to anticipate future events and take preventative action. AI generally enhances decision-making by strengthening its efficacy, reliability, and evidence-based basis[64].

3. **Reduced Workload:**

By automating time-consuming and repetitive tasks like data analysis, administrative work, communication, and decision support procedures, artificial intelligence greatly reduces the workload of employees. AI systems can help employees save time and effort by searching, processing, and analyzing vast amounts of data, interacting with customers through chatbots, and helping with task execution. AI-enabled tools also simplify internal communication, hiring, and training, which further reduces manual labor and boosts productivity. Employee engagement and productivity are positively impacted by this workload reduction, which eventually improves overall organizational performance, particularly in complex and dynamic (VUCA) environments[65].

4. **Increased Accuracy:**

By enabling accurate analysis of large and complex datasets while reducing human error, artificial intelligence (AI) dramatically increases the accuracy of managerial decision-making. AI systems use sophisticated algorithms to find correlations, patterns, and trends that human analysts might miss, producing more trustworthy and data-driven insights. Furthermore, by combining historical and current data, AI-powered predictive analytics improves forecasting accuracy, enabling managers to foresee results and make wise strategic choices. All things considered, this enhanced analytical capacity guarantees increased consistency, objectivity, and accuracy in decision-making procedures[66].

E. Challenges and Limitations:

1. Data Privacy Issues :

The terms "privacy," "security," and "trust" are interconnected in a way that links ethics and the law. The phrase "data privacy" refers to how information should be gathered, utilized, and accessed while taking legal rights into account [67]. Conversely, ethics refers to those obligations that occasionally turn into a duty to pursue [68]. Internet-based research is currently common in this technologically advanced era, and the majority of researchers use it extensively to accomplish the goals of data collection and analysis. Video conferencing for interviews, online surveys, "e-conversation" analysis, web page content analysis, discussion blogs, chat rooms, email, and more are all included in the category of Internet-based research [69].

2. High Cost :

Health systems that receive public funding must decide which interventions to buy and give to their patients. Nonetheless, decisions about how to allocate resources are made in light of the limitless demand for healthcare and the limited funds available to meet it. As a result, priorities should be established regarding what should be left to patients' private choices and what could be covered by public healthcare resources. Healthcare decision makers frequently prioritize and design interventions with the goals of enhancing overall population health, decreasing unfair health disparities, and increasing social efficiency [70]. The phrase "health inequality" describes variations in an individual's or a group's state of health. "Health inequality" refers to any quantifiable aspect of health that differs among individuals or socially relevant groups. Health inequity, on the other hand, is a particular kind of health inequality that indicates an unfair disparity in health. According to one common definition, it is unfair to permit inequality to continue since it represents avoidable and needless disparities. Accordingly, systematic disparities in health that could be prevented through appropriate measures are referred to as health inequities [71].

1. Lack of Training:

In order to achieve organizational goals, training and development initiatives are strategically implemented to enhance employees' knowledge and abilities. The word "training" refers to a type of education intended to improve particular job-related abilities in an employee's current role. However, "development" refers to a broader set of skills and knowledge intended for long-term professional growth and advancement within an organization [72,73].

2. Dependence on Technology:

The application of improved technologies in agriculture in developing nations raises a number of concerns for policymakers and interest groups. These include how infrastructure, institutions, and policies influence the uptake of new technologies and how they affect welfare and productivity. However, the majority of micro-level adoption studies are unable to address these crucial policy concerns. This article offers different strategies for creating technology adoption studies that will be helpful to policymakers, based on a thorough analysis of the literature on the adoption of agricultural technologies. It examines the general limitations of cross-sectional adoption studies conducted in a limited number of communities and talks about some of the challenges associated with carrying them out. Adherence to precisely defined terms that are standardized across studies, the use of sampling techniques that enable data from microstudies to be generalized to higher levels of aggregation, and a thorough analysis of the assumptions that frequently underpin such studies are among the recommendations [74].

F. Ethical and Legal Considerations:

1. **Patient Confidentiality:**

For a number of reasons, general practitioners encounter unique difficulties when it comes to confidentiality. A family member who is also a patient of the general practitioner may benefit from information about one patient. GPs offer their patients continuity of care across a variety of illnesses, both minor and major, as well as over time. They are more likely to be conscious of the social aspects of their patients' lives, such as whether their epileptic patient is a driver. Anyone who has accompanied the patient can see the GP patient record on the computer screen during a consultation, even if the patient is not aware of it. These and other instances show why general practitioners must understand the moral and legal obligations pertaining to patient confidentiality and how they affect their day-to-day work. This article examines recent General Medical Council (GMC) guidelines and their practical implications, as well as the ethical and legal framework within which health care professionals fulfill their duty of confidentiality [75].

2. **Accountability of AI Decisions:**

One of the most complex areas of current research is undoubtedly autonomous driving. To achieve the goal of a fully autonomous vehicle, numerous scientific fields and technological advancements are required. Since the vehicle's interactions in the real world are nondeterministic, it is impossible to definitively determine the vehicle's action sequences. Due to the high level of complexity of the driving task, even challenging driving situations require a high level of experience. By utilizing vast amounts of data, artificial intelligence (AI) and machine learning (ML) promise to address these kinds of issues. These massive volumes of recorded data can be thought of as the machine's experiences, which match a brain's prior experiences. Making decisions based on past experiences is not transparent or evident to outsiders, just like with humans. In the context of technology, opacity rises as system complexity does. But for the technology to be widely embraced by consumers and society, these obstacles must be removed (Amodei, 2016). In any event, every vehicle subsystem needs to be protected throughout the process to prevent mistakes that can happen both during development and during operation in order to guarantee acceptable products [76].

G. Future Perspectives:

1. **AI-Integrated Hospitals :**

Hospitals with AI integration are anticipated to change healthcare delivery into a highly data-driven, effective, and patient-focused system. In order to facilitate real-time data analysis, predictive diagnostics, and individualized treatment planning, future hospitals will make use of technologies like computer vision, machine learning, and natural language processing. To facilitate proactive decision-making and early disease detection, these intelligent systems will combine clinical imaging, wearable device data, and electronic health records. AI will also improve hospital workflows by automating resource allocation, administrative tasks, and robotic-assisted procedures. This will lessen the workload for clinicians and increase operational effectiveness. Crucially, rather than taking the place of medical professionals, AI is expected to enhance clinical accuracy while preserving human judgment and compassion. However, in order to guarantee inclusive and reliable healthcare systems, successful implementation will necessitate resolving issues with data privacy, ethical concerns, and equitable access.[77]

2. Smart Clinical Pharmacy Systems :

By combining advanced data analytics, machine learning, and clinical decision support systems, artificial intelligence (AI)-powered smart clinical pharmacy systems are anticipated to revolutionize pharmacy practice in the future. In order to detect drug-related issues, forecast drug demand, and suggest individualized treatment plans, these systems can automatically examine patient data, electronic health records, and medication histories. AI-driven platforms will improve patient safety and treatment results by enabling real-time detection of drug-drug interactions, allergies, and dosage errors. Furthermore, medication distribution will be streamlined, and operational inefficiencies will be decreased by smart systems that incorporate robotics, automated dispensing, and predictive inventory management. The use of AI chatbots and virtual assistants for patient counseling, enhancing medication adherence, and expanding access to pharmaceutical care are all included in the future outlook. All things considered, these intelligent systems will change pharmacists' roles from traditional dispensing to more patient-centered clinical decision-making, enhancing the effectiveness and quality of healthcare[78].

3. Expansion in India:

Strong government initiatives, growing startup ecosystems, and widespread adoption across various sectors are driving the rapid acceleration of artificial intelligence (AI) expansion in India. In order to promote inclusive and sustainable growth, national strategies like those put forth by policy bodies have given priority to important areas like healthcare, agriculture, education, smart cities, and mobility. Industries are increasingly incorporating AI technologies to boost output, facilitate data-driven decision-making, and enhance service delivery. Research, innovation, and skill development in the nation have been further reinforced by the emergence of AI startups, improvements in digital infrastructure, and programs like national AI missions. Furthermore, it is anticipated that AI will play a major role in India's economic expansion, possibly increasing GDP, changing employment trends, and boosting technological competitiveness worldwide. However, issues like inadequate infrastructure, a lack of qualified labor, and moral dilemmas continue to be major obstacles that need to be removed in order for AI to grow in India in a sustainable and fair manner[79,80].

CONCLUSION

With improved decision-making, medication safety, and operational efficiency, artificial intelligence has become a revolutionary force in hospital and clinical pharmacy, greatly improving healthcare outcomes. Precise drug therapy management, early adverse drug reaction detection, and individualized treatment plans are made possible by the integration of AI technologies. Although AI has many advantages, its successful application necessitates resolving important issues like data security, ethical dilemmas, high costs, and the requirement for qualified experts. It is anticipated that future developments in smart pharmacy systems and AI-integrated hospitals will further optimize healthcare delivery and advance patient-centered care. Therefore, to fully realize the potential of AI in clinical pharmacy practice, a balanced approach combining technological innovation with ethical and regulatory frameworks is necessary.

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