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A Review of Personalized Medicine Recommendation Systems

S.Akhila[1], G. Shirisha[2]
[1]Assistant Professor, Department of MCA, Megha Institute of Engineering and Technology for Women, Edulabad (Village), Ghatkesar (Mandal), Medchal District, Telangana –, India.
[2]MCA Student, Department of MCA, Megha Institute of Engineering and Technology for Women, Edulabad (Village), Ghatkesar (Mandal), Medchal District, Telangana –, India.

***Abstract* – The extraction of meaningful and valuable medical knowledge from large-scale healthcare data has become a major research focus for supporting clinical decision-making. Among these advancements, personalized medicine recommendation has emerged as a significant area of study, aiming to identify the most appropriate medications for individual patients based on their specific health conditions. Such recommendation systems assist healthcare professionals in making informed prescribing decisions while minimizing the risk of medication-related complications, thereby attracting considerable attention from the research community. This survey presents a comprehensive review of personalized medicine recommendation by first defining the problem and its fundamental objectives. It then systematically categorizes and analyzes recent recommendation approaches according to four major perspectives: multi-disease medicine recommendation, medicine recommendation using combination patterns, recommendation enhanced with additional medical knowledge, and recommendation driven by patient feedback. Furthermore, the survey discusses commonly adopted evaluation methodologies and performance metrics used to assess these recommendation models. Finally, it highlights the major challenges in personalized medicine recommendation and outlines promising future research directions and emerging development trends in this rapidly evolving field.**

Keywords - **Personalized Medicine, Recommendation Systems, Machine Learning, Artificial Intelligence, Precision Medicine, Clinical Decision Support Systems (CDSS)**

I. INTRODUCTION

Clinical Decision Support Systems (CDSS) have become an essential component of modern healthcare by assisting clinicians in improving treatment quality, minimizing medical errors, and optimizing healthcare expenditures. Among the various functionalities of CDSS, medicine recommendation has gained considerable importance as it supports healthcare professionals in selecting appropriate medications through the analysis of patient-specific clinical information. Appropriate medication selection is a critical factor in achieving effective treatment outcomes and improving patient recovery. Consequently, the development of intelligent medicine recommendation systems has attracted significant attention from researchers and healthcare practitioners.

Traditional medicine recommendation approaches primarily rely on manually designed clinical rules developed by experienced physicians in accordance with established medical guidelines. Although these rule-based systems are capable of providing standardized treatment recommendations for individual diseases, they often lack the flexibility required to generate personalized prescriptions for patients with complex medical conditions. Furthermore, constructing and maintaining such rule-based knowledge requires substantial clinical expertise, extensive time, and continuous updates, making these systems difficult to scale and maintain.

The widespread adoption of Electronic Health Records (EHRs) has transformed the availability of healthcare data by enabling the systematic collection of patient information, including diagnoses, prescribed medications, laboratory findings, vital signs, and treatment histories. Simultaneously, advances in artificial intelligence and deep learning have created new opportunities to extract meaningful knowledge from these large-scale medical datasets. These developments have significantly accelerated research on personalized medicine recommendation, allowing data-driven approaches to overcome many limitations associated with conventional rule-based systems.

Personalized medicine recommendation aims to identify the most suitable medications for individual patients by utilizing their historical and current clinical information available in EHRs. The objective is to provide clinicians with reliable treatment recommendations that reflect each patient's unique health condition while reducing the likelihood of inappropriate prescriptions. Modern recommendation models focus on learning disease progression patterns from longitudinal medical records, minimizing adverse Drug–Drug Interactions (DDIs), and assessing treatment effectiveness through advanced computational techniques. By supporting informed prescribing decisions, these systems contribute to improved patient outcomes, enhanced medication safety, and more efficient utilization of healthcare resources.

Considering the growing significance of this research area, numerous personalized medicine recommendation models have been proposed in recent years. Despite this rapid progress, comprehensive survey studies covering the major developments in this domain remain relatively limited. Moreover, personalized medicine recommendation is inherently interdisciplinary, requiring expertise in artificial intelligence, machine learning, healthcare informatics, pharmacology, and clinical medicine. This diversity of knowledge makes it challenging for new researchers to obtain a complete understanding of the field.

To address this gap, this survey presents a comprehensive review of personalized medicine recommendation from a unified perspective. Existing approaches are systematically categorized according to their underlying methodologies, strengths, and limitations. Additionally, commonly adopted evaluation strategies are discussed, current research challenges are identified, and potential future directions are highlighted. The survey aims to provide researchers and practitioners with a structured understanding of recent advancements while serving as a valuable reference for future research in intelligent personalized medicine recommendation systems.

II. LITERATURE SURVEY

The rapid advancement of Clinical Decision Support Systems (CDSS) and the increasing availability of Electronic Health Records (EHRs) have significantly accelerated research in personalized medicine recommendation. Several studies have proposed intelligent recommendation models that assist clinicians in selecting safe and effective medications by analyzing patient-specific clinical information, disease characteristics, historical treatment records, and pharmaceutical knowledge.

Early research primarily focused on developing recommendation systems for individual diseases. Chen et al. introduced a multi-criteria decision-making framework combined with domain ontology to recommend anti-diabetic medications. Subsequently, Chen et al. enhanced this approach by integrating fuzzy reasoning with ontology-based knowledge to improve treatment selection for diabetes patients. Mahmoud and Elbeh further developed an ontology-driven recommendation framework specifically for Type-2 diabetes, enabling individualized medication suggestions based on semantic medical knowledge. Similarly, Liu et al. proposed a patient similarity-based recommendation strategy that utilized data mining techniques to identify effective diabetic treatment plans, while Wedagu et al. incorporated prior medical knowledge to enhance recommendation accuracy and clinical reliability. Beyond diabetes, researchers have also developed disease-specific recommendation systems for cancer, epilepsy, hypertension, bone marrow transplantation, and drug-resistant tuberculosis, demonstrating the effectiveness of intelligent prescribing in specialized clinical scenarios.

As many patients experience multiple coexisting diseases, recent studies have shifted toward generalized medicine recommendation frameworks capable of handling multimorbidity. Zhang et al. introduced the LEAP framework, which generates medication combinations sequentially while considering treatment effectiveness and safety. Wang et al. proposed the Personalized Prescription for Comorbidity (PPC) model that jointly learns representations of patients, diseases, and medications to produce individualized prescriptions for patients with multiple health conditions. CompNet further improved medication recommendation by modeling relationships among medicines using graph convolutional reinforcement learning, enabling order-independent prediction of medication combinations. GAMENet incorporated graph-structured memory networks to capture drug-drug interaction knowledge and patient history simultaneously, whereas SeqMed employed Generative Adversarial Networks (GANs) to learn expressive patient representations for personalized medication prediction. More recently, SafeDrug explicitly modeled drug-drug interactions to recommend both effective and safe medication combinations, while MICRON utilized recurrent residual networks to capture medication changes across consecutive patient visits. Conditional Generation Network (COGNet) further extended this direction by generating medication combinations through conditional sequence generation rather than conventional multi-label prediction.

Another important research direction focuses on modeling medicine combinations instead of recommending drugs independently. Early systems such as CADRE recommended medications according to symptom similarity and collaborative filtering techniques. Gong et al. formulated medication recommendation as a link prediction problem by integrating Electronic Health Records with medical knowledge graphs, enabling heterogeneous representation learning across patients, diseases, and medicines. Reinforcement learning-based approaches further improved combination recommendation by optimizing treatment policies while simultaneously reducing adverse drug interactions. Dynamic treatment recommendation models based on recurrent neural networks and deep reinforcement learning have also demonstrated promising results by adapting prescriptions according to patients' evolving clinical conditions.

To improve recommendation quality, several studies have incorporated external medical knowledge into data-driven learning frameworks. Knowledge sources including DrugBank, ICD ontologies, pharmaceutical descriptions, and graph-based medical knowledge bases have been integrated with Electronic Health Records to provide richer semantic representations. Graph Neural Networks (GNNs), Graph Convolutional Networks (GCNs), and transformer-based architectures have been successfully employed to encode hierarchical relationships among diseases, medicines, and clinical concepts, resulting in more accurate and clinically meaningful recommendations. In addition to physician-oriented recommendation systems, researchers have explored patient-centered medicine

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recommendation based on user feedback and online reviews. Li et al. proposed the iDrug framework, which predicts medicine ratings by considering patient interactions together with geographical and temporal information within mobile social networks. Garg applied sentiment analysis techniques to patient drug reviews using machine learning algorithms to recommend over-the-counter medications, particularly during large-scale healthcare emergencies when direct medical consultation may be limited. These approaches demonstrate that patient experiences and review data can provide valuable supplementary information for personalized medicine recommendation.

Overall, existing research indicates that personalized medicine recommendation has evolved from traditional rule-based decision support toward intelligent data-driven frameworks that leverage deep learning, graph neural networks, reinforcement learning, knowledge graphs, and patient feedback. Although substantial progress has been achieved, ensuring medication safety, improving model interpretability, effectively handling multimorbidity, and providing highly personalized treatment recommendations remain important challenges that continue to motivate ongoing research in this field.

III. PROPOSED METHODOLOGY

The proposed personalized medicine recommendation framework is designed to support intelligent clinical decision-making by utilizing Electronic Health Records (EHRs) together with relevant medical knowledge to recommend appropriate medications for individual patients. The primary objective of the framework is to generate safe, effective, and personalized medicine recommendations based on a patient's historical medical records and current clinical condition.

Initially, patient information is collected from Electronic Health Records, which contain comprehensive healthcare data such as disease diagnoses, prescribed medications, laboratory reports, demographic information, vital signs, and treatment history. These heterogeneous medical records are preprocessed to eliminate inconsistencies, organize clinical information, and transform the data into a structured representation suitable for machine learning models.

The structured patient information is then utilized to represent the patient's health status across multiple clinical visits. Each admission consists of disease information and the medicines prescribed during that particular visit. Historical admission sequences enable the framework to capture disease progression, medication continuity, and temporal dependencies that influence future treatment decisions. By considering previous admissions together with the patient's current diagnosis, the recommendation model gains a comprehensive understanding of the patient's evolving medical condition.

To enhance recommendation quality, additional medical knowledge is incorporated into the framework. Drug-related information, disease associations, pharmaceutical knowledge, and drug-drug interaction data provide valuable contextual information that complements Electronic Health Records. The integration of structured medical knowledge improves the clinical reliability of the recommendation process while helping reduce unsafe medication combinations.

The processed patient information and medical knowledge are supplied to the medicine recommendation model for training and inference. During training, the model learns the complex relationships among diseases, medications, historical treatment patterns, and patient characteristics from large-scale Electronic Health Records. After training, the learned model predicts an appropriate set of medicines for new patients by analyzing their previous medical history and current disease information.

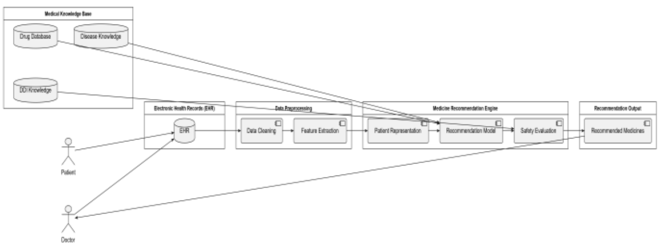

Figure 1. Overall System Architecture of the Personalized Medicine Recommendation Framework.

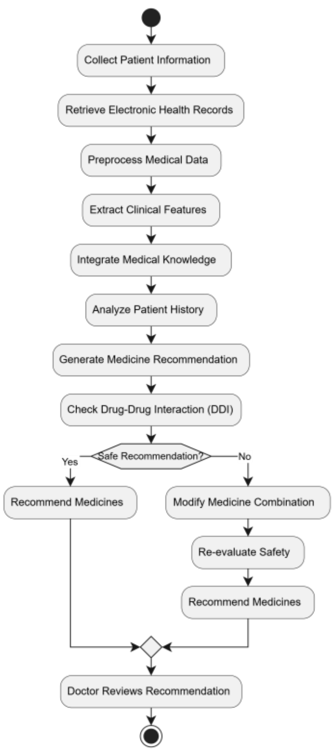

Figure 2. Activity Diagram of the Personalized Medicine Recommendation Process.

The recommendation process emphasizes both treatment effectiveness and medication safety. Besides accurately identifying medicines suitable for the patient's clinical condition, the framework also attempts to minimize adverse Drug-Drug Interactions (DDIs), thereby improving prescription safety and supporting clinicians in selecting optimal medication combinations.

Finally, the generated medicine recommendations are presented as clinical decision support rather than automated prescriptions. Healthcare professionals can use these recommendations as an additional reference while making final prescribing decisions. This approach combines data-driven intelligence with clinical expertise, contributing to personalized treatment planning, improved patient outcomes, enhanced medication safety, and more efficient utilization of healthcare resources.

IV. SYSTEM ARCHITECTURE

The personalized medicine recommendation framework follows a structured pipeline that transforms raw clinical data into reliable medication recommendations. The architecture begins with the acquisition of patient information from Electronic Health Records (EHRs), which contain diagnoses, prescribed medications, laboratory reports, demographic details, and previous treatment histories. These diverse clinical records serve as the primary source of information for the recommendation process.

In the initial stage, the collected medical data undergo preprocessing to eliminate inconsistencies, handle missing values, and convert heterogeneous healthcare information into a standardized format. Structured patient records are then generated by organizing diagnoses, medicines, and clinical observations into sequential admission histories that accurately represent the patient's medical progression.
Following preprocessing, relevant medical knowledge such as disease relationships, drug information, and Drug–Drug Interaction (DDI) knowledge is integrated with the structured Electronic Health Records. This additional knowledge enriches the patient representation and provides valuable clinical context for generating safer and more effective medicine recommendations.

The processed patient records and medical knowledge are supplied to the medicine recommendation engine. During the training phase, the recommendation model learns complex relationships among diseases, medicines, historical admissions, and treatment patterns using large-scale Electronic Health Records. The trained model subsequently performs inference on new patient records by analyzing both historical visits and current disease conditions to identify the most appropriate medication combinations.

The final stage of the architecture produces personalized medicine recommendations that prioritize both therapeutic effectiveness and patient safety. The generated recommendations are intended to support clinicians during prescription planning by providing evidence-based medication suggestions while minimizing the possibility of adverse drug interactions. This intelligent workflow improves clinical decision-making, enhances treatment quality, and contributes to personalized healthcare delivery.

V. RESULTS AND DISCUSSION

The performance of personalized medicine recommendation systems is generally assessed based on two fundamental aspects: effectiveness and safety. An efficient recommendation model should accurately predict appropriate medications while simultaneously minimizing the possibility of unsafe drug combinations. Therefore, both therapeutic accuracy and prescription safety are considered essential during model evaluation.

1. Effectiveness Evaluation
The effectiveness of a medicine recommendation model is determined by comparing the medicines predicted by the model with the actual prescriptions provided by medical professionals. Since physicians' prescriptions represent the ground truth, conventional evaluation metrics widely adopted in recommendation systems are employed to measure prediction quality.

Recall evaluates the proportion of relevant medicines successfully identified by the recommendation model, reflecting its ability to recover appropriate prescriptions.

Precision measures the correctness of the recommended medicines by determining how many predicted medicines actually appear in the physician's prescription.

F1-Score provides a balanced assessment by combining Precision and Recall through their harmonic mean, thereby offering a comprehensive measure of recommendation performance.

In addition to these metrics, the Jaccard Similarity Coefficient is frequently used to determine the similarity between the predicted medicine set and the actual prescription. A higher Jaccard value indicates greater overlap between recommended medicines and the medications prescribed by clinicians, demonstrating improved recommendation effectiveness.

2. Safety Evaluation
Besides prediction accuracy, medication safety is a critical requirement for personalized medicine recommendation systems. Patients suffering from multiple diseases often receive several medicines simultaneously, increasing the possibility of adverse Drug–Drug Interactions (DDIs). Consequently, recommendation models must generate prescriptions that are both clinically effective and pharmacologically safe.

The most commonly adopted safety metric is the Drug–Drug Interaction (DDI) Rate, which measures the proportion of predicted medicine pairs that are known to produce adverse interactions. Lower DDI rates indicate that the recommendation model generates safer medication combinations with fewer harmful interactions.

Overall, an effective personalized medicine recommendation system should achieve a balanced trade-off between recommendation accuracy and medication safety. While effectiveness metrics evaluate how closely the predicted prescriptions match clinical practice, safety metrics ensure that the recommended medicine combinations minimize potential adverse interactions, thereby supporting reliable and patient-centered clinical decision-making.

VI. CONCLUSION

This survey provides a comprehensive overview of recent advancements in personalized medicine recommendation systems and their role in supporting intelligent clinical decision-making. Initially, the personalized medicine recommendation problem is formally introduced, highlighting how patient-specific clinical information can be utilized to generate appropriate medication recommendations under different healthcare scenarios.

The survey systematically reviews existing approaches by categorizing them into four major groups: medicine recommendation for multi-disease patients, recommendation based on medicine combination patterns, recommendation enhanced with additional medical knowledge, and recommendation utilizing patient feedback. Each category is analyzed with respect to its underlying methodology, advantages, and existing limitations, providing a structured understanding of current research developments.

Furthermore, commonly adopted evaluation strategies are discussed by emphasizing two essential performance aspects: recommendation effectiveness and medication safety. Standard evaluation metrics, including Precision, Recall, F1-score, Jaccard Similarity, and Drug–Drug Interaction (DDI) Rate, are summarized to illustrate how personalized medicine recommendation models are assessed in practical healthcare applications.

Although significant progress has been achieved, several research challenges remain open, including improving medication safety, enhancing model interpretability, supporting dynamic and fine-grained treatment recommendations, and effectively integrating lifelong healthcare records into intelligent recommendation systems. Addressing these challenges will contribute to the development of more reliable, transparent, and patient-centered personalized medicine recommendation frameworks capable of improving healthcare quality and clinical outcomes.

VII. FUTURE ENHANCEMENT

The personalized medicine recommendation framework incorporates several enhancements that improve the quality, reliability, and clinical applicability of medication recommendation systems. By utilizing Electronic Health Records (EHRs) together with relevant medical knowledge, the framework is capable of generating personalized treatment suggestions based on individual patient characteristics rather than relying solely on generalized clinical guidelines.

One significant enhancement is the integration of longitudinal patient records, allowing the recommendation model to analyze historical admissions in addition to the patient's current diagnosis. This enables the system to capture disease progression and treatment continuity, resulting in more accurate and context-aware medication recommendations.

The framework also incorporates medical knowledge, including disease relationships, pharmaceutical information, and Drug–Drug Interaction (DDI) data, to improve recommendation safety. The inclusion of external clinical knowledge helps reduce the possibility of adverse medication combinations while increasing the overall reliability of prescription recommendations.

Another important enhancement is the ability to support patients with multiple coexisting diseases. Unlike conventional disease-specific recommendation systems, the proposed framework considers multiple medical conditions simultaneously and recommends appropriate medicine combinations that satisfy complex treatment requirements.

The recommendation process emphasizes both effectiveness and patient safety by evaluating medicine combinations using standard performance metrics such as Precision, Recall, F1-score, Jaccard Similarity, and Drug–Drug Interaction (DDI) Rate. This balanced evaluation strategy ensures that recommended medicines not only match clinical prescriptions but also minimize potential adverse interactions.

Furthermore, the framework supports intelligent clinical decision-making by providing recommendation results as decision-support information rather than replacing physicians' expertise. This collaborative approach allows healthcare professionals to combine computational intelligence with clinical judgment, leading to more personalized, reliable, and effective treatment planning.

Overall, these feature enhancements contribute to improved recommendation accuracy, enhanced medication safety, better utilization of Electronic Health Records, and more efficient delivery of personalized healthcare services.

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