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Advancing Personalized Medicine: The Integration of Genomic Data into Clinical Information Systems Through Artificial Intelligence and Machine Learning

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Abstract

Background: The integration of genomic data into clinical information systems is pivotal for advancing personalized therapy in healthcare. As medical knowledge expands, the need for sophisticated systems that can analyze and interpret genomic information is becoming increasingly critical.

Methods: This review evaluates current methodologies for integrating genomic data with clinical information systems, focusing on the implementation of artificial intelligence (AI) and machine learning (ML) algorithms. The review assesses various tools, including electronic health records (EHRs) and decision support systems, to enhance patient care through personalized treatment plans.

Results: Findings indicate that effective integration of genomic data can lead to improved risk stratification, optimized therapeutic regimens, and enhanced patient outcomes. The utilization of AI-driven predictive models demonstrates significant potential in forecasting disease progression and tailoring interventions based on individual genetic profiles. However, challenges such as data interoperability, ethical considerations, and regulatory hurdles remain prevalent.

Conclusion: The integration of genomic information into clinical workflows represents a transformative step towards personalized medicine. Continued advancements in AI and data management practices are essential to overcome existing barriers and realize the full potential of genomic data in clinical settings. Stakeholders must prioritize the development of standardized protocols to promote data sharing and ensure patient privacy.

Keywords: Genomic data, personalized therapy, clinical information systems, artificial intelligence, predictive models.

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1. Introduction

Artificial intellect (AI), an emerging field in computer science, is progressively used to do activities requiring human-like intellect, including complicated problem-solving, logical reasoning, and learning analysis based on extensive data sets. In healthcare, the importance of AI is paramount, especially in patient monitoring and telemedicine, where it is facilitating transformational advancements [1]. The rapid advancement of Natural Language Processing (NLP) algorithms is one of the most active areas in AI within healthcare. These advanced systems can interpret and understand human language, a capability that significantly impacts patient care. NLP, when used to assess symptoms described by patients, may promote more natural and effective communication, hence improving patient involvement and improve the entire telemedicine experience. A notable milestone is the use of computer vision algorithms for the analysis of medical imaging, including CT scans and MRIs [2]. By using AI to identify and classify illnesses from these photos, healthcare professionals may achieve more accurate and timely diagnosis. The advancements in machine learning are significant, as AI systems are trained on extensive data sets to discern patterns and provide predictions. This capacity may be used to examine extensive patient data, including vital signs and test results, to predict health issues and customize individualized treatment regimens. The emergence of AI-driven virtual assistants in telemedicine is transforming patient-provider interactions, providing patients with convenient access to healthcare information and resources, as well as facilitating efficient and personalized communication with healthcare professionals [3,4].

As AI transforms healthcare interactions, leading to more personalized, efficient, and accessible treatment, it is essential to emphasize patient safety and privacy in the development and implementation of AI systems. This review paper aims to provide a thorough overview of the current status of AI technology in patient monitoring and telemedicine, examining both the potential advantages and the problems these advances encounter. Furthermore, we want to provide counsel for academics, doctors, and policymakers to promote the prudent and efficient use of AI technology in healthcare.

2. Utilizations of artificial intelligence in healthcare

Virtual assistant chatbots may provide tailored medical assistance and education to patients according to their specific needs and preferences [5]. Through the use of Natural Language Processing (NLP) and machine learning algorithms, chatbots may adapt their replies based on patient interactions, aligning with the patient's language and style, hence enhancing the user experience to be more natural and engaging. Furthermore, virtual assistant chatbots provide 24/7 assistance, which is especially beneficial for patients who cannot reach healthcare practitioners during standard operating hours [6]. Chatbots, available 24/7, assist patients in acquiring necessary information and assistance at any time. Moreover, virtual assistant chatbots may provide tailored health information and recommendations depending on an individual's medical history and risk factors. They may evaluate a patient's medical data and provide customized preventative and treatment suggestions, guaranteeing that patients get the most suitable care [7]. Virtual assistant chatbots may provide tailored reminders and medical information, aiding patients in comprehending and adhering to treatment regimens. Nonetheless, further study is required to assess its efficacy in enhancing patient adherence and motivation. A chatbot may suggest nutritious meal plans or exercise regimens to diabetes patients, according to their dietary choices and physical activity patterns. Numerous online chatbots, including Your.MD, Your Symptoms, Babylon Health, AI Health, Iodine, and Molly, utilize artificial intelligence and machine learning to deliver tailored health information and assistance for minor ailments, chronic conditions, and mental health concerns [8,9].

Nonetheless, the implementation of virtual assistant chatbots continues to encounter certain constraints. In the United States, individuals' medical histories are often dispersed across many systems, complicating the access and integration of these information. Presently, AI encounters significant obstacles in executing these duties, such as data interoperability, standards, and integration problems. Primarily, data interoperability becomes a significant challenge. Patients' medical records may be housed in various electronic health record (EHR) systems that lack standardized processes, complicating data sharing and integration [10]. To resolve this issue, health information exchanges (HIEs) and data standardization protocols, such as HL7 FHIR, are perpetually advancing to enhance the smooth transmission of medical information across various systems. Furthermore, data harmonization is a significant problem. Diverse healthcare organizations and EHR systems may use varying data formats and coding schemes, hence complicating data integration. The same medical condition may be denoted by varying terminology and codes across multiple systems, complicating AI's ability to interpret and analyze this data. Addressing these challenges necessitates the development of standardized data protocols and coding methods across the industry. Moreover, data integration encounters both technological and policy obstacles [11]. Numerous healthcare organizations lack enough technological assistance for data management and exchange, or they may be reluctant to disclose patient data owing to privacy and security apprehensions. These issues further constrain the use of AI technology in the integration and analysis of fragmented patient data [12,13].

Notwithstanding these issues, virtual assistant chatbots provide significant promise in customized healthcare. By persistently enhancing data interoperability, standardization, and integration technologies, while addressing regulatory and technological obstacles, AI tools may more effectively assist patients, delivering more precise and tailored health suggestions.

3. Real-time patient surveillance and telehealth monitoring with wearable devices and sensors

Real-time patient monitoring and remote care may be facilitated by wearable devices and sensors, allowing healthcare personnel to continually monitor vital signs and other biometric data. Smartwatches may track a patient's heart rate and blood pressure, relaying this data wirelessly to a central monitoring station for analysis and interpretation by healthcare specialists [14]. Wearable sensors, a compact and portable alternative, can be affixed to the body or incorporated into apparel, jewelry, or other accessories to monitor vital signs and health metrics including heart rate, blood pressure, respiratory rate, blood oxygen saturation, body temperature, and physical activity, transmitting the data wirelessly to a central monitoring station for comprehensive analysis. Furthermore, smartphone apps may use integrated sensors and wearable devices to monitor patients' health in real-time, collecting data such as physical activity, sleep patterns, and food habits, while offering feedback and recommendations to assist in health management. Moreover, smart home gadgets such as smart speakers and thermostats may facilitate real-time monitoring of patients' health state. Employing wearable gadgets and sensors for real-time patient monitoring has several advantages for both patients and healthcare practitioners [15,16]. Patients may attain enhanced security and tranquility, aware that their health state is under surveillance and that any alterations in their condition may be promptly identified. For healthcare practitioners, it may enhance the comprehension of patients' health requirements and facilitate the monitoring of their condition's evolution, resulting in more individualized and focused therapy. Moreover, real-time patient monitoring with wearable devices and sensors may automate some monitoring duties, thereby alleviating the workload on healthcare workers and minimizing the likelihood of human mistake.

Nonetheless, there are significant obstacles linked to the use of wearable devices and sensors for real-time patient monitoring. The real-time monitoring process may produce a substantial volume of data, some of which may be challenging to evaluate and comprehend, particularly when integrating data from several sources in disparate formats. Furthermore, these wearable devices have significantly advanced in data collecting and self-monitoring; nonetheless, their accuracy remains constrained. Wrist-worn devices may be influenced by wrist positioning and user activity during blood pressure measurement, resulting in erroneous readings [17]. Conversely, upper-arm cuffs are often regarded as more dependable for blood pressure assessment. Consequently, while using AI tools dependent on such data, it is important to comprehend the limits of these devices and implement appropriate measures in practical applications to guarantee the efficacy and dependability of AI tools, thereby mitigating any dangers associated with erroneous data [18].

Certain data may be faulty or imprecise, presenting a risk of misjudgment. In healthcare, faulty or erroneous data may profoundly affect diagnostic and therapeutic choices. Research indicates that the precision of wearable devices in assessing physiological indicators, such as heart rate and blood pressure, may be influenced by the manner of use, user activity, and the device's inherent technological constraints. Moreover, integration challenges across various data sources may result in inconsistent or missing data, thereby impacting the performance and dependability of AI models. To resolve these difficulties, rigorous data validation and quality control protocols must be established to guarantee that the data used for AI model training and application has high quality and dependability. Consequently, healthcare providers and policymakers must acknowledge the limitations of these devices, implement requisite preventive measures in clinical applications, mitigate potential risks arising from inaccurate data, assist researchers, clinicians, and policymakers in comprehending and utilizing AI technology effectively, and guarantee that patients derive benefits from it [19, 20].

Moreover, there are possible threats to patient confidentiality and data protection. Unauthorized third parties might exploit sensitive information on patients' health and well-being if it is not sufficiently safeguarded. that tackle these difficulties, researchers are using AI-driven systems that scan extensive data from diverse sources, yielding useful insights for physicians. Additionally, anonymization and encryption technologies are used to enhance patient privacy and data security.

4. Models for forecasting illness development and categorizing patient risk

Predictive models for disease progression and patient risk stratification use machine learning algorithms to evaluate patients' medical histories, genetic data, and other information to forecast their risk of acquiring certain illnesses or the advancement of existing ailments. These models may also identify people at risk of acquiring certain illnesses, allowing healthcare practitioners to adopt preventive steps to mitigate risk. They are used to predict the advancement of patients' existing ailments, enabling healthcare practitioners to modify treatment strategies appropriately [21]. Predictive models are developed by training machine learning algorithms on extensive patient datasets, which encompass medical history, genetic information, and other pertinent data, to analyze and discern patterns and correlations that can forecast the likelihood of patients developing specific diseases. Predictive models for disease progression and patient risk stratification can identify individuals at risk of developing specific diseases and forecast the advancement of existing conditions, enabling healthcare providers to implement preventative measures and modify treatment plans to enhance the management of patients' current health statuses. A multitude of models has been used for the prediction and risk assessment of many illnesses [22]. Researchers have created deep learning models capable of predicting the evolution of Alzheimer's disease using brain MRI scans and other patient data, therefore assisting physicians in comprehending the illness's advancement and modifying treatment strategies appropriately. Cardiovascular disease risk prediction models use patient data, including blood pressure, cholesterol levels, and genetic information, to estimate the likelihood of heart disease, assisting physicians in identifying high-risk individuals and implementing early intervention strategies [23].

Cancer risk prediction models assess the likelihood of cancer based on patient data, including family history, lifestyle variables, and genetic information, enabling physicians to identify high-risk individuals and provide early therapies to mitigate their cancer risk. Risk prediction models for surgical complications can assess the likelihood of postoperative complications using patient data (including age, medical history, and type of surgery), enabling physicians to identify high-risk patients and implement enhanced monitoring or interventions to mitigate the risk of complications [24,25]. Readmission risk prediction models may anticipate the likelihood of patient readmission using variables such as age, medical history, and disease severity, therefore assisting physicians in identifying high-risk individuals and implementing enhanced surveillance or treatments to mitigate readmission risk. These are but a few instances of how deep learning is used to forecast disease development and assess patient risk stratification. With the growing prevalence of deep learning models in healthcare, we anticipate an increase in the use of predictive models to enhance patient care and outcomes.

Predictive models for disease development and patient risk stratification are essential tools in medicine, enabling healthcare professionals to proactively identify patients at high risk for certain diseases and to apply preventive measures. Although useful, the implementation of these models has issues related to the accuracy and integrity of the data used for training, along with possible systemic biases or mistakes in the predictive analytics [26]. To maintain the accuracy and integrity of these models, it is essential to carefully assemble high-quality, unblemished datasets for training and to continuously evaluate model performance to identify any hidden mistakes or biases that may undermine prediction results. The diligent implementation of these models is essential to prevent patients from experiencing unequal treatment based on predictions produced from the models. As the use of these models increases in clinical practice, continuous assessment of their performance indicators and a thorough examination of their therapeutic effects are essential to ensure their prudent and effective application. Furthermore, the datasets utilized for model training must accurately reflect the demographic under investigation, incorporating a variety of relevant patient information—demographics, genetic heritage, and environmental factors—to facilitate the creation of models that reliably predict disease progression and risk stratification across the entire patient population, regardless of individual backgrounds or characteristics. It is essential to guarantee that the use of such models complies with the highest ethical standards, supported by informed patient consent and reinforced by rigorous oversight and regulatory frameworks to prevent any potential misuse or discriminatory practices against specific patient populations [27,28].

5. Customized therapeutic suggestions derived on patient information

Customized therapy suggestions derived from patient data constitute a significant area in healthcare, since they may enhance patient outcomes and decrease medical expenses. Deep learning algorithms may analyze extensive patient data, including genomic, genetic, demographic, and lifestyle aspects, to ascertain patient responses to various therapies. Genomic data, including whole-genome sequencing, single-nucleotide polymorphisms (SNPs), and gene expression patterns, provide essential insights into the biological foundations of illnesses and individual therapeutic responses. This information may then be used to formulate individualized therapy suggestions according to the distinct features and medical history of an individual patient [29]. Researchers have created deep learning models that can analyze the genomic and genetic characteristics of a patient's tumor and forecast their response to different chemotherapy agents. These models may find particular biomarkers correlating with therapy success by integrating data on gene mutations, copy number variations, and epigenetic alterations. This information may then be used to prescribe the most effective treatment strategy for the patient, so enhancing their likelihood of a good result [30]. Likewise, deep learning algorithms may evaluate patient data, including age, medical history, and surgical type, in conjunction with genetic data, to forecast the likelihood of problems such as infections or hemorrhaging. This enables the suggestion of supplementary monitoring or preventive strategies for high-risk patients, therefore reducing their risk of problems and enhancing their overall results. Additionally, pharmacogenomic data may be used to anticipate adverse medication responses and refine drug dose, hence enhancing personalized patient care [31,32].

Pharmacogenomics is an advancing discipline that incorporates genetic data to improve medication treatment, examining how genetic variants influence therapeutic effectiveness and possible adverse effects, so greatly improving the accuracy of customized medicine. Deep learning algorithms may use pharmacogenomic data to forecast a patient's metabolic reaction to certain medications. Genetic differences in genes that encode drug-metabolizing enzymes, transport proteins, and drug targets affect drug concentration in the body and consequent treatment effects. By incorporating pharmacogenomic data, AI models may suggest the optimal medications and doses for individual patients, therefore reducing adverse effects and enhancing therapeutic efficacy [33].

Furthermore, pharmacogenomic data may assist in identifying individuals at risk of adverse medication responses, facilitating preventative interventions or alternate treatment approaches. This data-centric methodology guarantees that patients get secure and efficacious therapies tailored to their distinct genetic profiles. In cancer, pharmacogenomic profiling might inform the selection of targeted medicines that are more efficacious for individuals with certain genetic alterations. Incorporating pharmacogenomic data into tailored treatment strategies enables healthcare practitioners to attain superior clinical results and enhance overall patient care [34].

6. Automated appointment scheduling and notifications

Automated appointment scheduling and reminders are essential instruments in the healthcare industry, enhancing patient adherence and reducing the burden on healthcare personnel. With the ongoing advancement of deep learning models in analyzing extensive patient data, we may anticipate a growing prevalence of automated appointment scheduling and reminders in healthcare [35].

Automated appointment scheduling and reminders are essential instruments in healthcare, since they may improve patient compliance with treatment regimens and alleviate the workload on healthcare practitioners. Artificial intelligence (AI), particularly deep learning models, may enhance these procedures by evaluating extensive patient data to provide more precise and individualized suggestions. Deep learning algorithms may evaluate patient data, including medical history, prior appointment schedules, and preferences, to suggest optimal appointment times for each patient. This comprehensive analysis reduces the probability of missed appointments or rescheduling, resulting in improved results and enhanced efficiency within the healthcare system. AI may discern trends in patient behavior and appointment history that may be obscured in conventional scheduling systems, so enhancing the scheduling process to more effectively align with patient requirements and provider availability [36].

Furthermore, automatic appointment reminders are a crucial element of AI-augmented scheduling. Through the analysis of patient data, including demographics, medical history, and previous reactions to appointment reminders, deep learning models may identify the most successful reminder technique for each individual patient. This tailored strategy minimizes the incidence of missed appointments and guarantees that patients have the necessary treatment in a timely manner. AI may dynamically modify reminder techniques in real-time according to patient feedback, hence augmenting the efficacy of these reminders [37].

Examples of AI-enhanced automated appointment scheduling and reminders in practice include systems such as PatientPop, Zocdoc, and Vyasa. These systems use AI to assess patient data and suggest optimal appointment times based on patient history and prior appointment schedules. They dispatch automatic, customized appointment reminders to patients, enhancing the probability of attendance and required treatment. These AI-driven technologies provide effortless automated scheduling, enabling patients to conveniently book online and get reminders by text or email, thus enhancing overall patient adherence and alleviating the burden on healthcare personnel [38].

Studies indicate that automated appointment scheduling and reminder systems may enhance patient compliance in some circumstances. Research indicates that using text message reminders may significantly decrease the incidence of postponed medical appointments, therefore enhancing patient adherence. Another research indicates that email reminders have positively contributed to the enhancement of vaccination rates and follow-up visits [39]. Nonetheless, dependence only on reminder systems cannot adequately resolve compliance and motivation challenges. Patient adherence to treatment regimens is determined by several variables, including confidence in physicians, the connection with the healthcare system, and the efficacy of treatment models. With the ongoing advancements in AI and deep learning models, we anticipate a rise in the use of AI-driven automated scheduling and reminders in healthcare, resulting in enhanced patient outcomes and more efficiency in healthcare delivery.

7. The profound influence of artificial intelligence on the healthcare sector

Artificial intelligence (AI) is transforming several facets of healthcare, with numerous critical domains under present research and development scrutiny. Deep learning models are being used in medical imaging and diagnostics to aid in the identification and diagnosis of disorders in medical pictures, including X-rays, MRIs, and CT scans. AI systems are used to detect early indicators of cancer, cardiovascular ailments, and neurological issues with exceptional precision and rapidity. In personalized medicine, AI assists in the analysis of genetic, demographic, and lifestyle data to provide tailored treatment suggestions. This method is especially advantageous in cancer, since AI can forecast a patient's reaction to various chemotherapy agents, hence creating more effective and personalized treatment strategies. Predictive analytics and risk assessment represent a vital domain of AI research, whereby AI models are used to forecast patient outcomes, including the probability of disease progression, readmission rates, and probable surgical complication risks. These forecasts empower healthcare professionals to implement preventative strategies, improve patient care quality, and decrease healthcare expenditures. Natural language processing (NLP) technology is used to derive significant information from unstructured medical data, including clinical records and research publications. This technology enhances electronic health record (EHR) systems, optimizes administrative chores, and improves patient care via superior data usage [40].

8. Conclusion

The integration of genomic data into clinical information systems marks a significant leap toward the realization of personalized medicine. By harnessing the power of artificial intelligence and machine learning, healthcare providers can analyze complex genomic information to tailor therapies that align with individual patient profiles. This approach not only enhances treatment efficacy but also minimizes adverse effects associated with conventional one-size-fits-all strategies.

As evidenced by the findings of this review, the potential benefits of integrating genomic data into clinical practice are profound. Enhanced risk stratification can lead to timely interventions, thereby improving overall patient outcomes. Predictive models based on genomic data allow healthcare providers to anticipate disease progression and adjust treatment plans proactively, ensuring that patients receive the most appropriate care.

However, the journey toward fully realizing these benefits is fraught with challenges. Data interoperability remains a significant barrier, as patient information is often scattered across disparate systems. Establishing standardized protocols for data sharing will be crucial in addressing this issue. Furthermore, ethical considerations surrounding patient privacy and the use of sensitive genetic information cannot be overstated. It is imperative that healthcare institutions implement robust safeguards to protect patient data while facilitating the necessary flow of information.

In conclusion, the integration of genomic data into clinical information systems is not merely an enhancement of current practices; it represents a paradigm shift in how healthcare is delivered. By embracing technological advancements and addressing existing challenges, the healthcare industry can move closer to a future where personalized medicine is the norm, ultimately resulting in improved health outcomes for patients worldwide. Continued collaboration among researchers, clinicians, and policymakers will be vital in driving this transformation forward.

References

1. Esteva, A., Kuprel, B. & Novoa, R. A. Dermatologist-level classification of skin cancer with deep neural networks. Oncologie 19(11–12), 407–408 (2017).
2. Wiriyathammabhum, P. et al. Computer vision and natural language processing: Recent approaches in multimedia and robotics. ACM Comput. Surveys 49(4), 1–44 (2017).
3. Gulshan, V. et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. Jama-J. Am. Med. Assoc. 316(22), 2402–2410 (2016).
4. Susymary, J. & Deepalakshmi, P. Machine learning for precision medicine forecasts and challenges when incorporating non omics and omics data. Intell. Decis. Technol.-Netherlands 15(1), 69–85 (2021).
5. Aggarwal, A. et al. Artificial intelligence-based chatbots for promoting health behavioral changes: Systematic review. J. Med. Internet Res. 25, e40789 (2023).
6. Kurniawan, M. H. et al. A systematic review of artificial intelligence-powered (AI-powered) chatbot intervention for managing chronic illness. Ann. Med.

7. Abd Rahman, R. et al. Application of machine learning methods in mental health detection: A systematic review. IEEE Access 8, 183952–183964 (2020).
8. Calvaresi, D. et al. Exploring agent-based chatbots: A systematic literature review. J. Ambient Intell. Hum. Comput. 14(8), 11207–11226 (2023).
9. Bertagnolli, M. M. et al. The electronic health record as a clinical trials tool: Opportunities and challenges. Clin. Trials 17(3), 237–242 (2020).
10. Kiourtis, A., et al. Improving Health Information Exchange through Wireless Communication Protocols. In: 16th International Conference on Wireless and Mobile Computing, Networking and Communications (IEEE WiMob). Electr Network. (2020).
11. Nickel, B. et al. Words do matter: A systematic review on how different terminology for the same condition influences management preferences. BMJ Open 7(7), e014129 (2017).
12. van Panhuis, W. G. et al. A systematic review of barriers to data sharing in public health. BMC Public Health https://doi.org/10.1186/1471-2458-14-1144 (2014).
13. He, T. & Lee, C. Evolving flexible sensors, wearable and implantable technologies towards BodyNET for advanced healthcare and reinforced life quality. IEEE Open J. Circuits Syst. 2, 702–720 (2021).
14. Nguyen, T. N. et al. Guest editorial innovations in wearable, implantable, mobile, & remote healthcare with IoT & sensor informatics and patient monitoring. IEEE J. Biomed. Health Inform. 27(5), 2152–2154 (2023).
15. Hrabovska, N., Kajati, E. & Zolotova, I. A validation study to confirm the accuracy of wearable devices based on health data analysis. Electronics 12(11), 2536 (2023).
16. Wang, T.-L. et al. Assessment of heart rate monitoring during exercise with smart wristbands and a heart rhythm patch: Validation and comparison study. Jmir Form. Res. 7, e52519 (2023).
17. Mukkamala, R. et al. Evaluation of the accuracy of cuffless blood pressure measurement devices: Challenges and proposals. Hypertension 78(5), 1161–1167 (2021).
18. Zamani, E. D. et al. Artificial intelligence and big data analytics for supply chain resilience: A systematic literature review. Ann. Oper. Res. 327(2), 605–632 (2023).
19. Cai, Y. et al. Artificial intelligence in the risk prediction models of cardiovascular disease and development of an independent validation screening tool: A systematic review. BMC Med.
20. Lopez-Cortes, X. A. et al. Machine-learning applications in oral cancer: A systematic review. Appl. Sci.-Basel 12(11), 5715 (2022).
21. Mohsin, S. N. et al. The role of artificial intelligence in prediction, risk stratification, and personalized treatment planning for congenital heart diseases. Cureus J. Med. Sci.
22. D'Agostino, R. B. et al. General cardiovascular risk profile for use in primary care: The Framingham heart study. Circulation 118(4), E86–E86 (2008).
23. Zheng, Y. et al. Risk prediction models for breast cancer: a systematic review. BMJ Open 12(7), e055398 (2022).
24. Zeng, S. et al. Machine learning approaches for the prediction of postoperative complication risk in liver resection patients. BMC Med. Inform. Decis. Mak.
25. Monteiro Costa, M. L. et al. Development and validation of predictive model for long-term hospitalization, readmission, and in-hospital death of patients over 60 years old. Einstein-Sao Paulo https://doi.org/10.31744/einstein_journal/2022AO8012 (2022).
26. Yarborough, B. J. H. et al. Clinical implementation of suicide risk prediction models in healthcare: A qualitative study. BMC Psychiatry
27. Wiberg, H. M., Data-Driven Healthcare via Constraint Learning and Analytics. (2022).
28. Obermeyer, Z. & Emanuel, E. J. Predicting the future—Big data, machine learning, and clinical medicine. N. Engl. J. Med. 375(13), 1216–1219 (2016).
29. Liu, Z. et al. Effect of SNPs in protein kinase <i>Cz</i> gene on gene expression in the reporter gene detection system. World J. Gastroenterol. 10(16), 2357–2360 (2004).
30. Beam, A. L. & Kohane, I. S. Big data and machine learning in health care. Jama-J. Am. Med. Assoc. 319(13), 1317–1318 (2018).

31. Wang, C.-W., Khalil, M.-A. & Firdi, N. P. A survey on deep learning for precision oncology. Diagnostics 12(6), 1489 (2022).
32. Cuocolo, R. et al. Machine learning in oncology: A clinical appraisal. Cancer Lett. 481, 55–62 (2020).
33. McKillip, R. P. et al. Patient perceptions of care as influenced by a large institutional pharmacogenomic implementation program. Clin. Pharmacol. Ther. 102(1), 106–114 (2017).
34. Ryan, D. K. et al. Artificial intelligence and machine learning for clinical pharmacology. Br. J. Clin. Pharmacol. 90(3), 629–639 (2024).
35. Wang, Y. et al. DeepDRK: A deep learning framework for drug repurposing through kernel-based multi-omics integration. Brief. Bioinform.
36. Varnai, R. et al. Pharmacogenomic biomarkers in docetaxel treatment of prostate cancer: From discovery to implementation. Genes 10(8), 599 (2019).
37. Werner, K. et al. Behavioural economic interventions to reduce health care appointment non-attendance: a systematic review and meta-analysis. BMC Health Serv. Res.
38. Posadzki, P. et al. Automated telephone communication systems for preventive healthcare and management of long-term conditions. Cochrane Database Syst. Rev.
39. Bjornholt, K. et al. The effect of daily small text message reminders for medicine compliance amongst young people connected with the outpatient department for child and adolescent psychiatry. A controlled and randomized investigation. Nordic J. Psychiatry 70(4), 285–289 (2016).
40. Dombkowski, K. J. et al. The impacts of email reminder/recall on adolescent influenza vaccination. Vaccine 35(23), 3089–3095 (2017).

تطوير الطب الشخصي: دمج البيانات الجينية في أنظمة المعلومات السريرية باستخدام الذكاء الاصطناعي وتعلم الآلة

الملخص

الخلفية :يُعد دمج البيانات الجينية في أنظمة المعلومات السريرية أمرًا محوريًا لتطوير العلاج الشخصي في مجال الرعاية الصحية. مع توسع المعرفة الطبية، تزداد الحاجة إلى أنظمة متقدمة قادرة على تحليل وتفسير المعلومات الجينية بشكل فعال.

الطرق :تُقيّم هذه المراجعة الأساليب الحالية لدمج البيانات الجينية مع أنظمة المعلومات السريرية، مع التركيز على تطبيق خوارزميات الذكاء الاصطناعي (AI) وتعلم الآلة .(ML) كما تستعرض المراجعة الأدوات المختلفة مثل السجلات الصحية الإلكترونية (EHRs) وأنظمة دعم القرار لتحسين رعاية المرضى من خلال خطط علاج مخصصة.

النتائج :تشير النتائج إلى أن الدمج الفعال للبيانات الجينية يمكن أن يؤدي إلى تحسين تصنيف المخاطر، وتحسين أنظمة العلاج، وتعزيز نتائج المرضى. كما أظهرت النماذج التنبؤية المدفوعة بالذكاء الاصطناعي إمكانات كبيرة في التنبؤ بتطور الأمراض وتخصيص التدخلات بناءً على الملفات الجينية الفردية. ومع ذلك، تظل هناك تحديات مثل قابلية التشغيل البيني للبيانات، والاعتبارات الأخلاقية، والعقبات التنظيمية.

الخلاصة :يمثل دمج المعلومات الجينية في سير العمل السريري خطوة تحولية نحو الطب الشخصي. تُعد التطورات المستمرة في الذكاء الاصطناعي وممارسات إدارة البيانات ضرورية للتغلب على الحواجز الحالية وتحقيق الإمكانات الكاملة للبيانات الجينية في البيئات السريرية. يجب على الأطراف المعنية إعطاء الأولوية لتطوير بروتوكولات موحدة لتعزيز تبادل البيانات وضمان خصوصية المرضى.

الكلمات المفتاحية :البيانات الجينية، العلاج الشخصي، أنظمة المعلومات السريرية، الذكاء الاصطناعي، النماذج التنبؤية.