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Data Integration Challenges and Opportunities in Multi-Platform Health Information Systems: A Comprehensive Review

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Abstract

Background: As healthcare systems face increasing complexity due to aging populations, the prevalence of chronic diseases, and rising costs, there is an urgent need for innovative solutions to optimize care delivery. Artificial intelligence (AI) has emerged as a transformative force in predictive healthcare analytics, leveraging large datasets to forecast patient outcomes, stratify risk, and personalize treatments. This review explores the role of AI in advancing predictive healthcare analytics and its implications for clinical decision-making.

Methods: A comprehensive review of current literature was conducted, focusing on AI methodologies such as machine learning (ML) and deep learning (DL) applied to electronic health records (EHRs), imaging data, and wearable device outputs. The analysis evaluated the effectiveness of AI in diagnosing diseases, predicting clinical outcomes, and enabling personalized medicine. Attention was given to the ethical challenges and data integration complexities associated with these technologies.

Results: AI-based predictive analytics has demonstrated superior accuracy compared to traditional methods in areas such as early disease detection, patient risk assessment, and treatment optimization. Notable applications include AI-powered imaging for cancer detection, real-time monitoring of chronic conditions, and personalized treatment planning using large-scale EHR data. However, challenges such as algorithmic bias, data privacy concerns, and integration of AI systems across diverse healthcare platforms persist.

Conclusion: AI has the potential to revolutionize healthcare by enhancing the precision, efficiency, and personalization of patient care. Bridging gaps in data standardization, improving algorithmic transparency, and addressing ethical concerns are essential for realizing the full potential of AI in healthcare. Continued interdisciplinary collaboration will be pivotal in optimizing AI technologies for widespread adoption and improved patient outcomes.

Keywords: Artificial Intelligence, Predictive Analytics, Machine Learning, Personalized Medicine, Clinical Decision Support Systems

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1. Introduction

In the field of cardiovascular systems, current technology has progressed to enable the creation of completely individualized, high-resolution models of the whole heart. The VirtaMed virtual surgical training system, LaparoS, has pioneered the use of digital technology to simulate complex surgical situations (1,2). The University of Linkoping in Sweden has initiated an innovative study to explore the possibilities of digital twins in several facets of medical practice, including medical education, cardiac diagnostics, and medical implant design.

The progression of health care in modern society is apparent, characterized by a transition to a more technologically sophisticated methodology. The amalgamation of artificial intelligence (AI) with point-of-care sensors has transformed conventional in-person illness management into a digital format (3). Artificial intelligence, when integrated with digital technologies, may develop models that improve the efficiency, accuracy, and timeliness of medical treatment. In healthcare, DT provides a distinct viewpoint on self-quantification, possibly creating a new paradigm for illness treatment (4). Since 2017, Gartner's rising technology maturity curve has forecasted that digital transformation might attain a mature application status within the next 5 to 10 years. Currently, the novel uses of digital technology are revolutionizing the industrial sector.

DT has enabled the amalgamation of digital and physical environments over the whole lifespan of spacecraft (5). Moreover, the use of DT in collaborative painting robots has enhanced worker safety and health (6). Notwithstanding these developments, the use of digital technology in the medical industry remains constrained. According to reports, 47% of digital transformation applications are in the smart cities and urban spaces sector, 17% in the industrial sector, and a mere 1% in the medical sector (7). The use of digital technology in the management of chronic illnesses, such as diabetes mellitus (DM), is markedly deficient. Consequently, we have examined the literature on DT, delineating the main approaches and investigating the prospective uses of DT in DM therapy. Our objective is to predict forthcoming trends and trajectories in this domain.

2. The main methodologies of MeDigiT in diabetes management

A Medical Digital Twin (MeDigiT) is a system that integrates many data science techniques, each designed to forecast certain elements of a patient's health. Figure 1 illustrates that the DT cycle within the diabetes care pathway encompasses many strategies at each phase of diabetic mellitus (DM) therapy. This encompasses pre-illness management, disease management, and post-disease management. The amalgamation of varied data sources and the use of various methodologies for data collecting, modeling, and visualization is essential to the effectiveness of DT. During the pre-disease treatment phase, DT may evaluate an individual's risk of developing DM by examining variables such as obesity, physical inactivity, and genetic susceptibility. This facilitates the use of prophylactic measures to avert the development of diabetes mellitus. Healthcare practitioners may leverage the DT counterpart for individuals already diagnosed with DM to provide individualized treatment choices. For example, any irregularity in blood glucose levels identified by real-time glucose monitors may be sent to the DT system, which can then modify the insulin dose appropriately (2,7).

Regarding post-disease treatment, DTs may forecast diabetic consequences, including cardiovascular disease, renal failure, and visual impairment during follow-up appointments. Nonetheless, despite the encouraging technological improvements, problems persist in attaining an optimum digital transformation system. Vocabulary ambiguity in electronic medical records (EMRs) is a prevalent concern. Variations in body imaging, especially in soft tissue imaging resulting from differing patient postures, gestures, or movements, might cause discrepancies in the anatomical DT. The functional simulation techniques for physical digital twins remain intricate and time-intensive, obstructing prompt feedback. Moreover, apprehensions about patient data confidentiality and the absence of medical accountability in decision-making by digital technologies remain. These problems highlight the need for more study and development in the domain of DT (8).

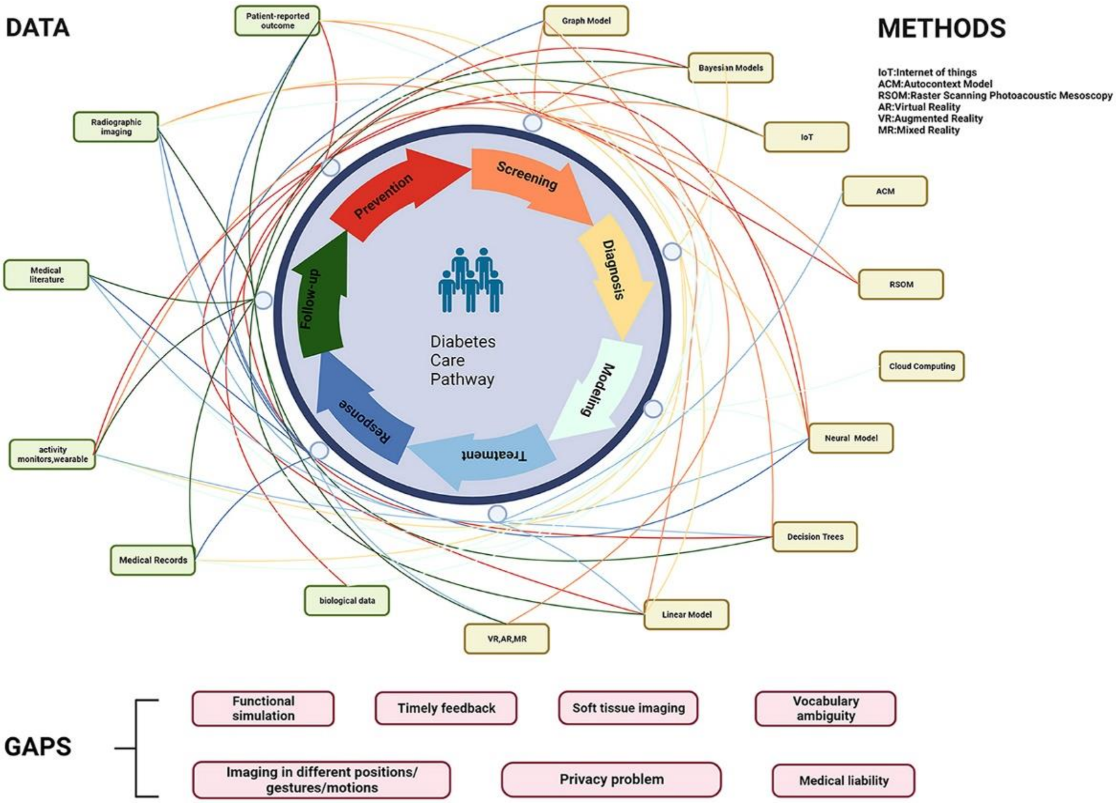

Figure 1. Data and methodologies used in the diabetic care pathway's decision-making cycle.

3. The procurement and amalgamation of diverse, multi-source healthcare data

The implementation of digital transformation in healthcare starts with the collection of diverse, multi-source patient data. The advancement of sensor technology has enabled the integration of data from wearables, medical imaging, and electronic medical records into a unified platform. This extensive data integration allows healthcare workers to provide more effective patient care. MeDigiT can digitize and quantify an individual's data across several levels in the domain of data collecting. Biological samples from T2DM patients may provide high-throughput sequencing data and expression profiles using several omics approaches, including genomics, transcriptomics, proteomics, and epigenomics (9–11). The enhancement and refinement of medical imaging methods have also supplied a dependable data source for MeDigiT.

Philips has introduced HeartModel, a device that mimics each frame of the heart cycle, therefore delivering essential information for therapeutic strategy (12). Continuous biosignals, obtained via wearable devices, are essential for health monitoring. Microsoft has introduced an Internet of Things (IoT) application platform that effortlessly integrates diverse medical wearables with IoT central instances. This platform facilitates the oversight and administration of devices by tailoring rules to particular device data and activating relevant alarms. Furthermore, lifestyle data (including food, smoking, alcohol use, and drug use), environmental data (encompassing living and working situations), electronic medical records, mobile applications, social media, and wearable devices all augment the data repository for MeDigiT. Due to the complexity, variety, and magnitude of this data, efficient methods are necessary to amalgamate these multi-source data streams (13).

4. Digital modeling and simulation

The MeDigiT system, derived from patient data gathered via sensors, medical treatment facilities, electronic medical records, and more sources, may be used to customize interventions and treatments while tracking patient reactions. Pfizer has used AnyLogic software to aid clinicians in modeling and assessing optimum medication doses for peripheral neuropathy. Digital modeling and simulation methods are essential instruments for precisely representing and modeling a patient's state. Anatomical models of the body and internal organs, produced using 3D modeling software like Mimics, Simpleware, and 3dSlicer, are essential for physicians in the diagnostic process (14). Biomechanical models of blood arteries, muscles, and bones provide physicians with the physical processes required to compute and assess full-cycle and full-field dynamic simulations. Virtual reality (VR) simulation systems have been created for tailored procedures, including percutaneous coronary intervention (PCI). These technologies integrate the patient's heart dynamic model to connect the physical realm with the virtual environment (15).

Ilya et al. (16) modeled the coronary vascular system of the human heart to facilitate the treatment of cardiac illness. MeDigiT is capable of developing physiological models using signals from the Internet of Things (IoT). In conventional cardiac radiofrequency ablation surgery, physicians have had to hypothesize all potential heart problems owing to technological constraints. They would thereafter eliminate certain disorders by administering electrical stimulation to the patient's heart to get an accurate diagnosis. Wu et al. (17) created a model-based cardiac radiofrequency ablation procedure assistance system that used decision trees to identify potential heart problems throughout the diagnostic phase using cardiac electrophysiological models. In addition to these models, biochemical models may replicate the operations of several systems, including the endocrine system and the liver. Simulation is essential for advanced model-based analysis, training, and forecasting. Digital modeling and simulation are often used together, with simulations conducted on the model.

5. Decision-making and artificial intelligence

The whole potential of MeDigiT cannot be achieved without the incorporation of AI. According to Robert Hayward, “Clinical Decision Support Systems (CDSS) connect health observations with health knowledge to impact clinicians' health decisions for enhanced healthcare.” CDSS are computerized systems that integrate patient clinical data with a knowledge repository, assisting medical personnel in diagnosing diseases and optimizing treatment strategies. By facilitating interventions in the diagnostic and therapeutic processes, Clinical Decision Support Systems (CDSS) may mitigate medical mistakes and improve the quality of care. AI technology allows MeDigiT to fulfill its decision-making goals, including description, diagnosis, and prediction. There are two main approaches for facilitating decision-making. The first method involves an expert knowledge base that reflects the decision-making process of physicians based on their expertise. The system derives decision rules and evaluates patient data as variables to assess the patient's condition and formulate conclusions. This method enables the computer to do enumeration and reasoning tasks, presenting the results in a manner consistent with the physician's competence. Thus, clinicians may provide precise choices with the system's support, using explanatory reasoning principles. The alternative decision-making approach encompasses machine learning, using the most recent deep learning (DL) methods.

Zhang et al. (18) created a deep neural network model that elucidates the link between contexts using risk code keywords. A validated analytical strategy for creating therapy pathways was established using

27,904 diabetic patients. Although these strategies may significantly aid physicians in decision-making, medical choices are complex and sometimes accompanied by ambiguity. When judgments pertain to moral and ethical dilemmas, it may be difficult for physicians to articulate their rationale. In response, behavioral artificial intelligence technology (BAIT) has been developed. BAIT can forecast the likelihood of a patient's condition, aiding physicians in decision-making within certain circumstances.

6. Evaluation and Regulation

The amalgamation of patient data, gathered by several sensors, with AI and IoT technologies, may enable the development of MeDigiT. This digital twin may model anticipated outcomes and aid physicians in clinical decision-making, facilitating the transmission of treatment feedback to the patient in the physical realm (19). During therapy, the MeDigiT model may be updated in real-time to represent the physiological changes in patients. This feedback technique enables the Digital Twin to create a closed-loop connection between the physical and virtual realms (20). A controlled experiment in South Korea evidenced the efficacy of this method in controlling diabetes patients using mobile phone glucose monitoring and feedback systems. The research indicated that patients who received feedback had improved glucose control (21). Electronic biofeedback treatment employs contemporary electronic devices to transform bioelectricity into auditory, visual, and other signals for patient rehabilitation.

Song et al. (22) validated their MeDigiT via a combination of man, machine, and environment to provide dynamic human-machine interaction. Besides its essential function in clinical therapy, feedback may also be used in the context of virtual candidate medications employed in drug testing. The Swedish Digital Twin Consortium (SDTC) has proposed a strategy that involves two steps: first, creating unlimited replicas of network models encompassing all molecular, phenotypic, and environmental factors pertinent to disease mechanisms in individual patients; second, computationally administering thousands of drugs to these digital twins to determine the most effective treatments. Ultimately, medications chosen by DTs are administered to actual patients as feedback (23). Alaris exemplifies a MeDigiT that does virtual assessments to determine whether pharmaceuticals may inhibit cancer cell proliferation. The findings indicated that everolimus, often authorized for breast and kidney cancer treatment, seemed effective for mucosal cancers resistant to chemotherapy, immunotherapy, and radiation, decreasing the proliferation rate of cells to 15% (24).

Moreover, to enhance patient compliance and access to chronic illness care, digital therapies (DTx) have arisen as a novel strategy to overcome the constraints of conventional medication. DTx is a software-driven, evidence-based intervention approach that can treat, manage, or control diseases. It may be performed alone or in combination with pharmaceuticals, medical apparatus, or alternative treatments. Digital therapeutics (DTx) may convert established medical concepts, recommendations, or conventional treatment regimens into application-based therapies. In essence, MeDigiT aids clinicians in using big data and enhancing its usefulness for clinical decision-making by offering improved feedback to patients on their disease trajectory.

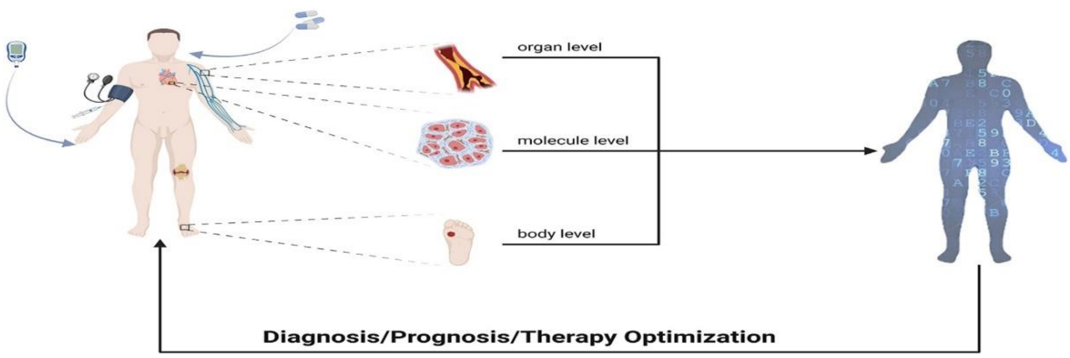

Figure 2. Illustration of the applicability of digital technology in diabetes patients across several scales.

7. The use of MeDigiT for diabetes control across many scales

Diabetes mellitus is a multifaceted illness influenced by several variables, including genetic predispositions, immunological dysfunctions, microbial infections, associated toxins, free radical toxins, and psychosocial elements. These variables may result in metabolic abnormalities, including hypoglycemia and insulin resistance, leading to consequences such as renal, ocular, and podiatric failure. MeDigiT, a dynamic digital representation of the patient, aids healthcare workers in comprehending a patient's medical condition and delivering individualized treatment for diabetes mellitus patients. MeDigiT provides a comprehensive framework for the management of chronic conditions, including diabetes mellitus. For diabetic patients, complications arising from diabetes mellitus are a significant cause of disability or mortality, making the treatment of diabetes mellitus critically important. Research indicates substantial enhancements in self-care among multiple myeloma patients who engaged in a hybrid model of online and offline health education, facilitating ongoing illness management and complication avoidance (24). MeDigiT has significant potential within the whole disease care continuum, functioning as a fundamental element at various scales for diabetes patients (Figure 2).

MeDigiT is integral to diabetes control via dietary regulation, physical activity, and insulin efficacy. Thamotharan et al. (25) developed a human digital twin (HDT) framework and IoT architecture for the individualized treatment of Type 2 Diabetes Mellitus in elderly persons. The framework integrates deep learning models and mathematical models with diverse patient data to customize insulin delivery depending on the patient's varying conditions. Deployment and testing have shown that HDT is efficacious in the individualized control and treatment of diabetes mellitus. Twin Health similarly offered whole-body digital therapeutics for diabetes management by monitoring patient sensor data and providing individualized advice (26). Shamanna et al. (27, 28) conducted a twin precision therapy (TPT) program for individuals with diabetes hypertension to enhance insulin resistance and manage hypertension.

The program used the Twin mobile application, continuous glucose monitors (CGM), Fitbit Charge 2 sensor watch, digital Bluetooth-enabled blood pressure monitor (TAIDOC TD-3140), and Powermax BCA-130 Bluetooth Smart Scale to collect and evaluate physiological data from diabetes mellitus patients. It developed a MeDigiT that dynamically illustrates the metabolic condition of the diabetes mellitus patient and offers tailored therapies. Presently, a "metabolic DT" (MDTwin) personalizes insulin dose and delivery patterns for patients by evaluating individual glycemic reactions to a high-fat, high-protein diet to get ideal blood glucose levels. Furthermore, familial dietary habits and diverse educational and environmental information will be documented, and a decision tree may be developed around the individual if required. MeDigiT can use diverse data and information to evaluate the state of the human body and provide a tailored evaluation (29).

Expert knowledge systems provide the automated execution of health evaluations and illness diagnoses, with the resultant information sent to the patient for further enhancements. The MeDigiT system allows the physician to oversee the diabetic patient's status, facilitating precise and prompt diabetes care. The Cleveland Clinic (30) executed a pilot randomized controlled trial (RCT) of DT precision treatment, which delivers meticulous management of nutrition, activity, and sleep through trained health coaches via an app and telephone, ensuring that daily average blood glucose levels remain consistently within the optimal range. In the randomized controlled trial, the DT platform was used to acquire individualized multidimensional patient data, and the TPT treatment system was included to provide accurate nutritional recommendations. Consequently, the findings are anticipated to provide a foundation for the use of MeDigiT in the treatment and management of diabetes mellitus at the patient level.

Diabetes mellitus is often linked to several chronic consequences, such as blindness, atherosclerotic disease, and diabetic foot. Alongside the development of a complete MeDigiT for diabetes management, it is also possible to make particular organ twins to avoid and address diabetes problems. Pathological alterations at the organ level are conventionally identified and evaluated by medical imaging. Nonetheless, with the emergence of MeDigiT, digital reproductions may be created to mimic and recreate the affected organs. These individualized models are essential for strategizing and determining a suitable solution. Orcajo et al. presented a foot twin that may be used for enhanced diagnostics, customized therapies, and mitigation of intervention risks to optimize therapy after the evaluation of novel surgical techniques (31).

Moreover, the use of MeDigiT may aid doctors in formulating optimum therapeutic regimens for patients with chronic heart failure (32). The Living Heart Project, created by Dassault Systèmes, a French software firm, encompasses all facets of heart function (such as blood flow, mechanics, and electrical impulses) to assist physicians in forecasting patient outcomes. Siemens has created a cardiac DT model anticipated to replicate a patient's heart, including size, ejection fraction, and muscular contraction. The DT of a patient's heart allows real-time monitoring of cardiac function, enabling the physician to get quick feedback and offering the patient an accurate prognosis and targeted therapy.

Biogenetic traits may be directly inherited from one's grandparents. Simultaneously, the sequenced genetic information of a person and their progenitors will be documented in real-time, and any medical assessment performed by a healthcare facility will be sent to the network with the subject's agreement. Cells, the fundamental structural and functional elements of the human body, contain genetic information. With the progression of life observation technology to the single-cell level, MeDigiT may be used for the segmentation, identification, and tracking of stem cell pictures, demonstrating higher accuracy and recall in stem cell image segmentation compared to phase difference methods (33). Li et al. (34) developed a MeDigiT framework using dynamic single cells, which can prioritize the upstream regulator (UR) gene of biomarkers and drug development based on the dynamic alterations of MeDigiT in seasonal allergic rhinitis.

Chen et al. (35) introduced a novel virtual cell experimental framework to create the human Ensemble Cell Atlas (HCA) system, a cell-centric human cell graph. The ACA facilitates drug experimentation on virtual human cells, hence enhancing drug development efficiency and decreasing the expenses associated with human clinical trials. Type 1 diabetes mellitus and severe type 2 diabetes mellitus result from the loss and dysfunction of pancreatic β-cells, resulting in insufficient insulin production (36). Certain research has revealed molecular biomarkers for diagnosing diabetes mellitus state, with the capability to detect diabetes mellitus (37). The EU's OPTOMICS initiative integrates photoacoustic imaging phenotyping and multi-omics to enhance diabetes management, validating a MeDigiT model that elucidates the static and dynamic processes in T2DM development through the amalgamation of molecular biomarkers and the non-invasive technique known as raster scanning optoacoustic microscopy (38).

The MeDigiT model, integrated with a comprehensive molecular phenotype of the person at the DNA, protein, and metabolite levels, enhances the prediction and early detection of illness, hence increasing the overall probability of prevention. The ILET bionic pancreas is an innovative insulin delivery device that attains peak blood medication concentration rapidly by insulin injection combined with continuous glucose monitoring (39). The clinical efficacy, advantages, and cost-effectiveness of MeDigiT in the molecular therapy of DM are significant. This method has considerable promise for advancing the treatment and investigation of DM in the future.

8. The constraints and apprehensions of MeDigiT in diabetes treatment

The implementation of MeDigiT depends on the collection and synthesis of many data sources, which necessitates interoperability solutions. In the integration of extensive biomedical data, standardization serves as a crucial method for unifying and normalizing multi-source heterogeneous data in non-standard forms to enhance later use and analysis. The Health Level Seven (HL7) standard has been issued to provide interoperable access to patient data (40). This standard facilitates the coordinated access and sharing of integrated and collaborative data use across various information systems, devices, applications, and programs, transcending institutional, regional, and national borders. An AI model forecasts the 5-year risk of end-stage renal disease in Type 2 Diabetes Mellitus by using data from electronic medical records, facilitating the preparation of unstructured data by the HL7 standard (41).

The execution of MeDigiT poses a considerable problem for privacy infringements, including societal and ethical implications (42, 43). Achieving interoperability entails the capability for multi-platform communication and information exchange. Data sharing requires a rigorous ethical examination to safeguard patient privacy. External assaults may jeopardize the program code and endanger the patient's welfare or even life. Healthcare providers or any institution maintaining a comprehensive, longitudinal record of an individual's biological, genetic, physical, and lifestyle data presents a substantial privacy threat (44). Consequently, it is essential to get unequivocal agreement from stakeholders when handling this data. Cybercriminals may use genetic information from gene repositories to facilitate illicit actions. If DNA can be acquired via cybercrime, there is a possibility that offenders may deposit DNA samples at the crime site (45).

Consequently, to address security concerns such as medical data protection, user platform security, and network security, the implementation of a security management system is essential. Moreover, operating highly secure and sensitive software must provide immunity to disruptions and loss of medical data access during software upgrades. To address privacy concerns, numerous methods may be used for encryption, including passwords, fingerprints, and iris recognition. Access to or modification of the MeDigiT should be permitted only to a physician or professional with the requisite authorization (46).

The application of MeDigiT may exacerbate the pre-existing individual disparities among individuals, including health, lifespan, and strength. An athlete's performance, augmented by prolonged training, nutrition, and lifestyle choices, may be equivalent to that of an individual who has boosted their abilities via the use of doping substances. This presents an inequity issue in competitive environments. When this discrepancy is extended to society as a whole, one may get extensive data about an individual's genetics, metabolism, lifestyle, and more. For instance, if MeDigiT forecasts that an individual is predisposed to a certain illness, it may enhance healthcare; but this outcome will become integral to the person's identity and may ultimately affect societal perceptions, categorizing them as “sick.” Moreover, MeDigiT may further intensify existing socioeconomic disparities. Individuals having the financial means to pay for services might get information that may be inaccessible to others by using MeDigiT for treatment testing. Wealthy nations with MeDigiT research and development facilities and corresponding intellectual property may exacerbate the disparity between affluent and impoverished countries. If the creation and design of the DT exhibit prejudice related to race and gender, patients may experience discriminatory treatment (47).

9. Conclusion

In summary, digital twin (DT) technology is an evolving paradigm centered on data, with models as the foundation and software as the medium. It involves the representation of the physical world, diagnostic analysis, progressive enhancement toward predictive capabilities, and ultimately, decision-making processes. In healthcare, MeDigiT offers the benefits of cost reduction, less reliance on animal testing, and enhanced disease prevention. Its popularity will persist, and its present trajectory will intensify with advancements in AI and computer technology. To achieve the objective of completely using MeDigiT in diabetes care, more advancements are required in data integration, modeling and simulation, decision-making, and feedback and control mechanisms.

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دور الذكاء الاصطناعي التحويلي في تعزيز تحليلات الرعاية الصحية التنبؤية: الآثار على الطب الشخصي واتخاذ القرارات السريرية المحسّنة

الملخص

الخلفية :تواجه أنظمة الرعاية الصحية تعقيدات متزايدة بسبب شيخوخة السكان، وزيادة انتشار الأمراض المزمنة، وارتفاع التكاليف، مما يستدعي الحاجة الملحة إلى حلول مبتكرة لتحسين تقديم الرعاية. لقد ظهر الذكاء الاصطناعي (AI) كقوة تحويلية في تحليلات الرعاية الصحية التنبؤية، من خلال الاستفادة من مجموعات البيانات الكبيرة للتنبؤ بنتائج المرضى، وتصنيف المخاطر، وتخصيص العلاجات. تستكشف هذه المراجعة دور الذكاء الاصطناعي في تعزيز تحليلات الرعاية الصحية التنبؤية وآثاره على اتخاذ القرارات السريرية.

الطرق :تم إجراء مراجعة شاملة للأدبيات الحالية، مع التركيز على منهجيات الذكاء الاصطناعي مثل التعلم الآلي (ML) والتعلم العميق (DL) المطبقة على السجلات الصحية الإلكترونية(EHRs) ، وبيانات التصوير، ومخرجات الأجهزة القابلة للارتداء. قامت التحليل بتقييم فعالية الذكاء الاصطناعي في تشخيص الأمراض، وتوقع النتائج السريرية، وتمكين الطب الشخصي. تم إيلاء اهتمام خاص للتحديات الأخلاقية وتعقيدات تكامل البيانات المرتبطة بهذه التقنيات.

النتائج :أظهرت تحليلات الذكاء الاصطناعي التنبؤية دقة تفوق الطرق التقليدية في مجالات مثل الكشف المبكر عن الأمراض، وتقييم مخاطر المرضى، وتحسين العلاجات. تشمل التطبيقات الملحوظة التصوير المعتمد على الذكاء الاصطناعي للكشف عن السرطان، والرصد في الوقت الحقيقي للحالات المزمنة، وتخطيط العلاجات الشخصية باستخدام بيانات السجلات الصحية الإلكترونية على نطاق واسع. ومع ذلك، لا تزال التحديات مثل التحيز في الخوارزميات، ومخاوف الخصوصية المتعلقة بالبيانات، وتكامل أنظمة الذكاء الاصطناعي عبر منصات الرعاية الصحية المتنوعة قائمة.

الخاتمة :يمتلك الذكاء الاصطناعي القدرة على إحداث ثورة في الرعاية الصحية من خلال تعزيز دقة وكفاءة وتخصيص رعاية المرضى. إن سد الفجوات في توحيد البيانات، وتحسين شفافية الخوارزميات، ومعالجة المخاوف الأخلاقية أمر ضروري لتحقيق الإمكانات الكاملة للذكاء الاصطناعي في الرعاية الصحية. سيكون التعاون المستمر بين التخصصات محورياً في تحسين تقنيات الذكاء الاصطناعي لاعتمادها على نطاق واسع وتحسين نتائج المرضى.

الكلمات المفتاحية :الذكاء الاصطناعي، التحليلات التنبؤية، التعلم الآلي، الطب الشخصي، أنظمة دعم اتخاذ القرار السريري