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# Digital Twin - An Innovative Strategy in Healthcare Transformation: An Extensive Review

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## ABSTRACT

**In an age where the physical and digital worlds progressively intersect, the concept of the digital twin has aroused as a transformative force across various industries. Digital twins are dynamic digital imitations of physical objects; systems are procedures that can be used to simulate, analyse, and optimize their real-world analogue. In the health care field, a lot of work has gone into establishing digital twin of patient and medical devices. The digital twin of the patient is created by digitising the patient's physical traits and bodily alterations. Real-world utilization of this technology includes accurate maintenance, advanced operational efficiency, and support for well-informed decision-making, all of which are trans-formative. The digital twin revolution is changing how healthcare professionals approach patient care, treatment planning, and facility administration. Digital twins provide instantaneous monitoring, personalized therapy, and predictive analytics by generating dynamic virtual replicas of patients, medical equipment, and healthcare systems. By offering insights on energy use, material consumption, and other vital variables, digital twin facilitates improved resource management and boosts businesses by cutting costs and waste. Digital twins are positioned to play a vital role in modern healthcare, inciting innovation and efficiency throughout the sector as technology advances. We focused on applications and development of digital twin in healthcare sector by analyzing a large number of studies from distinct medical sector, the effectiveness of digital twin in imaging studies and diagnosis, cancer, cardiology, neurology has been discussed in this review.**

***Keywords***- Digital twin, Healthcare, Technology, Patient**.**

## I. INTRODUCTION

The idea of digital twin was first proposed by Grieves and Vickers in 2013.A Digital Twin, as the name suggests, is a virtual copy of a physical asset, procedure or system intended to replicate its real-world equivalents near real-time [1]. The concept of Digital twins has been getting significant recognition in recent years, particularly as advancements in technology continue to drive innovation across various industries. As the Digital and physical worlds converge, Digital twins have developed into a potent tool that can transform how we approach product design, manufacturing and maintenance processes. This research paper aims to explore the potential of Digital Twins for future generations, highlighting their applications, benefits and challenges that must be addressed to fully realized their potential [1]. This process allows for a continues feedback loop between the physical and digital realms, enabling a deeper understanding of an asset's performance and driving improvements efficiency, sustainability and overall operation. **Fig. 1.1** is a basic diagram showing how a digital twin operates in the health care industry.

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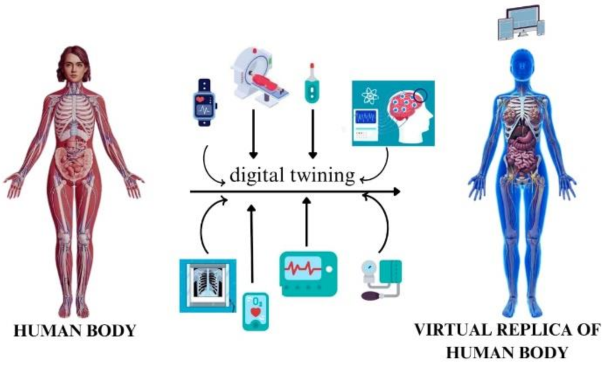


**Fig. 1.1: Basic concept of digital twin in healthcare.**

The concept of the Digital Twin, while seemingly new, has roots stretching back to early computer simulations in manufacturing and even NASA's Apollo program [3]. While that term itself emerged in the 2000s, advancements in IoT, cloud computing, sensor technology and big data analytics have propelled its evolution. Today, Digital Twins are key enablers of industry 4.0 and are finding applications in diverse fields beyond manufacturing, with their potential continuing to expand alongside technological advancements [4].

Digital Twins are used by General Electric (GE) to maximize performance on its wind turbines. Using real time data, they built virtual versions of the turbines to track their health, anticipate maintenance requirements and increases efficiency [2]. Singapore created a computerized replica of the whole city. To assist Municipal planners in making decisions on infrastructure, urban growth and crisis management, this model incorporates data from the variety of sources, including traffic, whether and energy use [5]. Digital Twins have been utilized by Philips in patient monitoring systems. They can more accurately identify health concerns and customized treatment strategies by digitally capturing patient's vital signs and medical histories. Digital Twins are used by Tesla [6].

This technology provides a complete perspective of individual health issues and operational efficiency by integrating data from several sources, such as imaging systems, wearable sensors and electronic health records. With increasing sophistication, Digital Twins possess the capacity to revolutionize health care delivery by improving diagnosis accuracy, optimizing treatment results and fastening breakthroughs in medical research and facility management. Data integration is a major obstacle, as its necessary to use real time data from several sources, sometimes in different forms, to create an accurate Digital Twin. Although challenging, ensuring the precision and integrity of this data is essential. he modelling and analysis of a Digital Twin can require significant computer resources, particularly for big and sophisticated systems, which presents another hurdle in terms of computational complexity [7]. Since digital twins might be the subject of cyber-attacks that compromise critical data or interfere with operations, cyber security is another important issue. Furthermore, the smooth integration and expansion of Digital Twin technology may be impeded by the absence of common protocol and compatibility across many platforms and systems. Finally, some organizations may find the initial cost and continuing upkeep to be expansive, which makes it difficult to realize a return on investment [8].

Digital Twins have the potential to be very economical, with substantial advantages that frequently exceed the initial outlay. Digital Twins encourage predictive maintenance by offering a real time virtual representation of physical assets, minimizing downtime and averting expansive equipment breakdowns. Proactive maintenance may save a significant amount of money by maximizing asset performance and extending its life span. According to David Williamson, CIO of San Diego-based health sciences business Abzena, who formerly worked in IT manufacturing and employed Digital Twins, a Digital Twin provides near-real-time visibility into the operation of assets and facilities. Supervisors are also able to see more details thanks to this enhanced visibility, such as how well employees are performing on an assembly line. Manufacturing supervisors can use Digital Twins to find issues with their manufacturing processes, according to Karen Panetta, an IEEE fellow and Dean of graduate education at Tufts Universities engineering school in Medford, Massachusetts. Additionally, users can use Digital Twin technology to see how their facility might operate in the future if a particular alteration is made. Prescriptive analytics, for instance, can recommend actions to take to ensure that a process is completed as quickly as feasible if the most crucial factor in a given scenario is producing a product as soon as possible [9].

Digital Twin technology does, however, have many potential drawbacks. Leaders in manufacturing should be aware of these problems so they can plan ahead and ideally avoid them. It may be simpler for businesses to produce a Digital replica when they are developing new factories, procedures or goods. However, before they can create Digital Twins in an economical way, companies with current IT infrastructure might need to upgrade their current systems. The functioning of Digital Twins might be adversely affected by low data quality, as these models depend on accurate data to function. Digital Twins and the implementation process may prove to be more costly for organizations than anticipated. It is imperative for manufacturing leaders to ensure that they are only implementing Digital Twin technology in appropriate processes rather than considering the technology as a Panacea [9].

Another industry where Digital Twin may be used is health care. From an application stand point,

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Digital therapeutics (DT) can handle patients as isolated, virtualized resources that can be utilized in contexts and circumstances where healthcare organizations are dealing with several interconnected strategic resources [7].

An extensive number of promising ongoing studies on Digital Twin are currently under research. The current review centers on the applications of Digital Twin in healthcare and its various studies. The current state of knowledge, research priorities regarding Digital Twins application have been discussed. Additionally, we describe a potential treatment that integrated Digital Twin in medical sector which shows that it has a potential to change the future of Health care. The focus is on how Digital twin can help and take account of challenges in medical sector.

## II. DIGITAL TWIN IMPLEMENTATION IN VARIOUS MEDICAL FIELDS

### *1. Medical imaging and diagnostic:*

The integration of virtual imaging simulations into medical diagnostics represents a pivotal advancement in patient-specific assessments. By employing Digital Twin technology, healthcare professionals can generate accurate, real-time replicas of a patient's anatomy, facilitating enhanced visualization during imaging procedures.

Digital twin will be one of the substantial 6G services in the 2030s [10]. With enhanced technologies such as analytics, artificial intelligence and Internet of Things (IoT), digital twins are evolved as simulated twins of real-world objects. The ability to inspect physical elements in real-time through digital twins can considerably decrease maintenance efforts [11]. In clinical care, a digital twin can be the simulated models of a person, which offers ongoing data and offer suggestions for variety of clinical based queries [12]. It implements data extraction and statical algorithms to produce precise outcomes with continued updating of data extraction [13]. In the next decade, virtual twin sector value will reach a $75.44 billion [14]. In the US, the digital twin sector was appreciated at USD 3.1 billion two years ago, and it is estimated to expand to USD 48.2 billion by 2026 [15].

In radiology, Digital Twins of devices such as CT and MRI machines could enable remote analysis of counterparts and, in real-time diagnose faults and even use AI technology to prevent issues before they arise, which serves as a guide for patients and health care providers to ensure the continuity of care [16,18].Such technology can support radiology service structure by upgrade patient care, reduce operating expenses, and enhance the care quality [17,18].Digital Twin could be viewed as a four-dimensional representation of a radiology department[18].

Digital Twin in Covid condition: The severe acute respiratory syndrome corona virus 2(SARS-CoV-2), also known as the corona virus or COVID-19, first surfaced in December 2019 and has since infected millions of individuals worldwide. Radiological facilities are in high demand-CT scan and X-RAY machines are widely used for examining the infection in patients [18,19]. The developed system is combined with medical machines and devices to utilize and capture details on the configuration, maintenance history and current state of health of that device [20]. Examination of COVID-19 infection with X-ray imaging using digital twin shown in **Fig. 1.2**

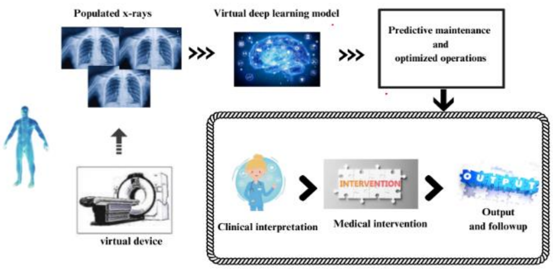


**Fig. 1.2: An analysis and detection approach for COVID-19 in X-ray pictures is envisioned, leveraging the fully developed digital twin idea.**

Pilati *et al.*, developed a Digital Twin by combining physical and virtual devices systems and performing real-time monitoring of patients flow to construct a vibrant, long lasting immunization facility [21]. Digital Twins contribution to the COVID -19 pandemic was discussed in [22].X-ray images are classified into pneumonia, SARS-COV-2 and normal images by utilizing the Convolutional Neural Network (CNN) [23]. The Residual Neural Network (RNN) models to analyze chest X-RAYs for detecting viral and bacterial pneumonia [24]. Pathak et al. analyzed contaminated cases using CT-scans through deep learning model [25]. Using chest CT scan data, SARS-COV-2 cases were differentiated with the assistance of CNN [26]. Hossain et al. presented a health care system-based AI to diagnose corona virus by collecting data from X-rays and CT scan images [27]. Multi-layer fusion-based model for SARS-CoV-2 and non- SARS- CoV2 classifications were displayed by Muhammad *et al.*, through the application of images recorded from an ultra sound machine [28]. Shorfuzzaman *et al.*, proposed a Neural Network system that used contrastive learning to recognize SARS-CoV-2 in X-RAY images [29]. At present, researches utilize Internet of Things for smart health care frame works [30-32].

Convolutional Neural Network: Convolutional Neural Network (CNN) have been developed to help with task like categorizing images and recognizing objects. Since 2D because of the way CNN is built, it cannot distinguish between those with Alzheimer's disease (AD) and those who have moderate cognitive impairment (MCI). To address this problem, Bijen-

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Khagi *et al.*, have adjusted the idea of categorizing patient based on their 3D MRIs while retaining the ability to incorporate the 2D features produced by the CNN frame work [33,34].

***2. Cancer research on digital twin:***

The community of Envisioning Computational Innovations challenges for Cancer was Established in the year of 2019 by the national cancer Institute and by the Several government national Laboratories, and an association of academic and industrial partners with aim of defining forward-looking approaches for speeding up predictive oncology. Here is the digital twin of cancer patient concept began to take form. The comprehensive implementation of digital twins Cancer patient requires contributions from the experimental, computational and Clinical committees. Making personalized treatment decisions for patients with Cancer patient digital twin could significantly advance predictive oncology. The evaluation, advancement and ultimate demand of Cancer patient digital twins in clinical settings and its have the potential to fundamentally alter the way complies illnesses such as cancer are addressed and treated [35].

Prognosticating patients according to their individual condition, predicting the outcome of therapy and distinguishing between benign and malignant malignancies are all made easier by mathematical models this is very promising initiative. Given the intricate relationships between genetics, cell signaling and metabolic pathway in cancer biology, data integration in particularly crucial. Systems biology seeks to develop mathematical representations of biological processes that match and anticipate their real occurrence [36]. In November 2013, Mark AJ Chaplain *et al*., Worked on a tumor growth of the mathematical model and treatment reaction. It forecast each patient's response to different dosage regimens or treatment combinations in silicon trials the study explains the tumor growth of mathematical model and host interactions. The past few decades, Investigation on cancer has incorporated many mathematical models. This work demonstrated how basic mathematical models may be developed, compared to experimental data and then used to replicate intricate biological processes and interaction [37]. **Fig. 1.3** describes risk and response prediction in cancer patients using digital twin.

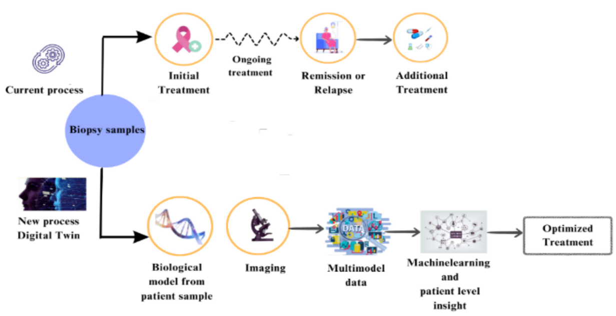


**Fig. 1.3: Using digital twins to forecast cancer patients' risks and responses.**

Guillermo Lorenzo *et al.*, 2022 study on virtual tumor modeling-In clinical Oncology using biological pictures and mechanism-based modeling to create practical digital twins. His primary focus in this work is mathematical models on developing intricate that capture the variety of tumors, the interactions between treatment and the micro-environment and other facets of the intricate growth of tumors [38].

Research on predicting treatment response and resistance-Simulated treatment learning (STL), the reaction of the patient's models to an alternative therapy by involving individuals who had distinct therapies but shared genetic tumor profiles. When Simulated treatment learning was used to evaluate two sets of Gene expression datasets for multiple myeloma that contained different medications (bortezomib and thalidomide), it was found that Simulated treatment learning could forecast the advantages of both therapies. For instance, thalidomide demonstrated a three-fold improvement in progression free survival and bortezomib a two-fold advantage. It enables more customized treatment. The major objectives of the authors are to identify potential causes of resistance and predict the response of each patient to different therapies. Digital twins assist in more accurate therapy selection, personalized dosage and yearly detection of treatment failure [39].

A study on optimizing Radiotherapy planning was done by Airbag Chaudhary, Graham Nash *et al.*, In order to enhance clinical decision making for cancer therapy this work offers a novel technique for building data driven predictive Digital Twins. The study focuses on high-grade gliomas, a kind of brain tumor with highly variable responses to standard radiotherapy. i) Initialization: The digital twin starts with a mathematical model of tumor growth, using the population level data to set initial parameters. ii) Personalization: Using Bayesian Calibration, the model is then customized for each patient by integrating their own MRI data. iii) Optimization: The best course of treatment for radiation therapy is chosen to use this customized Digital Twin. This involves balancing two competing goals: Maximizing tumor control (Reducing tumor growth risk) and Minimizing treatment toxicity. Creation of virtual models of 100 patients with high grade glioma by the proposed Digital Twin framework to simulate growth of the tumor and the treatment response. Personalized treatment regimens Result in a median increasing the time of tumor progression is around 6 days compared to standard Therapy. Additionally, optimal treatment options from the Digital Twin framework can led to move 16.7% in a median reduction in radiation dose while maintaining the tumor control level in the same as standard treatment. In these options it also provides increased doses for patients with aggressive cancer, where standard treatment might not be effective in controlling the tumor [40,41].

The goal of the Shmulevich group's effort is to generate Digital Twins of patients with acute myeloid

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leukemia (AML) by utilizing routinely gathered clinical data. In order to maximize patient-specific treatment strategies, this model seeks to forecast medication responses and treatment toxicities in advance [42].

The ongoing projects, using Digital Twins of 1 million pancreatic cancer patients to develop precision medicine treatment plans and increase long term survivability [43,44].

"Parameterized input from actual patient trajectories for treatment sensibility and resistance"-1 million pancreatic Cancer patient Digital Twin can be simulated in a model repository. This was done by the Senior investigator, Matthew McCoy, Ph. D., Assistant professor, George Town university's innovation center for biomedical informatics [43,44].

"Digital Twin approach for monitoring treatment response and resistance". The objectives are to proposed the most effective therapy paths for a given cancer patient, which can be chosen by utilizing a dynamic, Multistage Digital Twin created by combining the patient's personal data with data from other patients with the same condition to explore the treatment pathways space. The investigator involved in this study is Oliver Revert., Ph. D stand-ford university, Assistant Professor of medicine [43,44].

"The dynamic multi-scale Digital Twin for a patient with lung cancer"- Its goal is to create a customized digital twin which will be the first working model for non-small cell lung cancer in order to determination of the best course of therapy and enable adaptive treatment monitoring by utilizing data from recent test and the population. This was ongoing by the investigator, Qi Wang., Ph. D a professor of Mathematics in the university of South Carolina [43,44].

"Prototyping a self-learning Digital Twin platform for personalized treatment in melanoma patients"-This project had the goal to quickly prototype a 3D multi-scale model of melanoma metastases that will interact with the post event system in the presence or the absence of therapy (Autologous vaccine immunotherapy) and conform that the model accurately represents a wide range of patient trajectories which is clinically relevant. Paul Macklin., Ph. D Indian university associate professor of Engineering in Intelligent systems, is the investigator in this case [43,44].

"My Virtual Cancer"-Its main objective is to utilize biological, biomedical and EHR datasets to build a Digital Twin platform that incorporates mechanistic machine learning and Stochastic modelling techniques the investigation will assess the effectiveness of the Digital Twin for both common and rare diseases by focusing on 2 types of cancer: Breast cancer and Uveal. And the investigator of this study is Mali Shahriyari., Ph. D Assistant Professor, Mathematics and computer science, University of Massachusatts Amherst [43,44].

Every study focuses on a specific area of digital twin research that aims to progress the creation of a personalized the cancer patient model over the course of the next 2-3 years. By utilizing mathematics, active learning and ensemble model approaches, these studies have the potential to result in models and simulations that are particular to diseases and interventions [43,44].

The largest personalized medicine program in Spain-Computer simulations of study participants who are female patients with breast, lung or colon cancer are called digital twins. Miguel Quintet, a researcher the National cancer Research Institute (CIO), claims that these models will aid in "predicting the course of the disease of future patients and evaluating in a personalized way the effectiveness of the treatments". It was headed by the National cancer Research Institute (CIO) in collaboration with the CHRIS Cancer foundation, research facilities, medical facilities and universities. Public financing of 2.5 million euros has been given to it [45]. The application machine learning and Digital Twining in this case study on breast cancer highlights the potential of this technology to transform breast cancer diagnosis and therapy giving patients access to more precise and effective care [46].

With the help of temperature data, the proposed Digital Twin office a customized tool for breast cancer diagnosis. Based on the Bio heat concept, it is developed offline. During the online phase, the user connects to the Digital Twin and the Digital Twin updates its behavior according to temperature data. The findings demonstrate that there is insufficient temperature data to draw a suspicious conclusion. The outside temperature, Blood Pressure, Body Mass Index and Anatomy are just a few of the numerous variables that might affect once's body temperature. The temperature data and additional information gathered from smart linked devices are updated to compassionate for these discrepancies, making the Digital Twin precise in reflecting the behavior of body temperature. Personalized medication will be possible via Digital Twin, which is a major advancement [47].

***3. Digital twin in cardio-vascular disease:***

By Creating a Virtual copy of a patient's Cardiovascular system, Researches can simulate numerous physiological instance and interventions, thereby enhancing our understanding of the disease advancement.

A Cohort study established by Mei-di Shen *et al.,* [48]. That utilized Digital Twins to assess the five-year combined cardiovascular outcomes of 2173 virtual patients who received spironolactone treatment or where not treated found no statistically significant differences between the groups.

Phyllis M. Thangaraj *et al.,* [49] studied, two Randomized clinical Trials were digitally twined. First, the systolic Blood Pressure Intervention Trials (SPRINT) compared the effects of standard care (goal systolic blood pressure < 140mmHg) and intensive blood pressure control (Goal systolic Blood Pressure < 120mmHg) on the occurrence of major cardiovascular and vascular events. The trail comprised 9361

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participants {Median age 67(61-76[25-75%IQR]} and 3332 (36%) women.

Carlijn M. A. Buck *et al.,* [50] demonstrated that a MI Patient's Digital Twin will be more individualized, taking into account heart mechanics, electrophysiology and geometry while tracking minor changes in relation to the yearly collected data. The potential for multiple cardiac events following an infraction, such as re-infraction, the beginning of ventricular tachycardia's (VT), or even mortality, will likely be output by this Digital Twin. The doctor may choose to begin using a Digital Twin to test for ventricular tachycardias when the model indicates a high likelihood of ventricular tachycardias. The digital twin can be an essential tool in the disease management cycle by helping to treat cardiovascular diseases on several levels displayed in **Fig. 1.4**

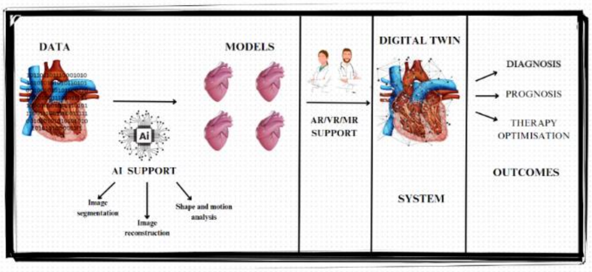


**Fig. 1.4: Is a simple schematic that illustrates the use of a digital twin in the cardiovascular outcomes**

Amir-Houshang Omidvar *et al.,* [51], introduced the development of Digital Twin starts with the recognition and the explanation of a medical issues such as the prediction of cardiac issues in a patient with Hypertension during the perinatal period. More through follow up with these people may be beneficial due to this data driven link, since it may be used to monitor and possibility avoid poorer outcomes like cardiovascular disease.

Katia Capellini *et al.,* [52,53] proposed a study which compared a result of the surgery with the preoperative stimulation of a specially designed endograph implanted in a patient. The patient specific structural finite element analysis, which has the ability to predict the placement of a custom made endograft for the treatment of ascending pseudo-aneurysm was evaluated in the current investigation using Digital Twin.

Rogelio-Gamez *et al.,* [52,54]. Proposed the platform which makes use of the inbuilt sensors that edge devices already have, such as smart phones and their ability to pair with external sensors in order to collect bio-signals via Bluetooth. Data gathered from sensors, medical records, social networks and external sensors is used to generate a cardio twin. Consequently, this data is analyzed to identify and support the idea that the real twin is suffering from an ischemic heart disease or a Stroke.

Ilya Naplekov *et al.,* [52,55] presented a study which shows that a Digital Twin of coronary vessels can give a virtual depiction of the weakening phase and the development of heart disease. It is possible to investigate qualitative models of coronary artery system mechanical characteristics, including laminar and turbulent blood flow as well as the effect of thrombus-induced vortex flow on load, blood pressure and valves.

Lasse Jagschies *et al.,* [56,52] used Digital Twin technology to exhibit a personalized model of a failing heart, vascular system and bi-ventricular assist device (BiBAD) implant design in his study. The model is a particularly helpful tool for the dimensioning of emerging ventricular assist device (VAD) technologies and future treatment methods in heart failure due to its capacity to link integral hemodynamic variables to local tissue mechanical deformation.

Matthias A F Gsell *et al.,* [52,57] displayed a study where anatomical twining was performed on 12 subjects using clinically obtained magnetic resonance images. By comparing the gold standard by domain ECG model with the underlying fast forward ECG model, a forward Saltelli sampling approach was then use to accomplish the functional twining of Ideal parameters for a single patient based on a clinically attained 12 lead ECG.

Jintai Chen *et al.,* [58], introduced a fresh outlook learning strategy in order to produce personalized ECG DTs to examine the heart conditions of diagnose individuals. This improves the understandings of the personalized heart diseases prospectively while maintaining the confidentiality of model development.

***4. Neurological disorder and research in digital twin:***

An important marker for diagnosing stroke at the beginning is Electroencephalography (EEG) monitoring, which is thought to be able to detect neurological dysfunction, a prevalent problem seen in the stroke population. To develop a digital twin for stroke patients, this study intends to demonstrate the viability of a "Digital twin" in the healthcare industry using Electroencephalography data and machine learning algorithms. Along with 75 healthy individuals, they looked as 48 stroke victims who had been admitted to a rehab facility. Using frontal, central, temporal, and occipital cortical electrodes, portable Electroencephalography devices were utilized to record Electroencephalography. Theta and delta activities, as well as the revised brain-symmetry score, are significant factors for dividing stroke patients and healthy people into different motor and cognitive state categories, according to the statistical study. Support vector machines (SVM) identified the Electroencephalography feature datasets with 76% accuracy using machine learning techniques. This healthcare digital twin framework may help in clinical decision-making for stroke preventive measures and post-stroke treatment [59].

In this work, experiments have been conducted using publicly available datasets from the University of Oxford, the Cerrahpasa Faculty of Medicine, Istanbul

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University [65]and others. These datasets contain voice samples collected from 195 subjects [65] which can be used to analyse and predict Parkinson disease at an early stage. These skilled datasets are used for verifying their proposed model; later by using the testing datasets, the performance of the proposed version will be analysed. The paper is divided into 5 sections. Section II give a literature review of the different digital twin-based healthcare systems active on the markets, a comparative analysis of the healthcare industry with and without digital twin features, and different classifier models associated in Parkinson disease hypothesis. Section II give a elaborate discussion of the proposed DTHS architecture with appropriate modelling of the K-Nearest classifier. In Section IV, two benchmark datasets under experimental evaluation are summarised with remarkable results and discussion. The final Section V gives the conclusions and future advancements of the research work [60].

Together, the project's authors produced a Direct Acyclic Graph (DAG) and a first set of 20 DELPHI statements, each of which had six corresponding sub-statements that summarized the pathophysiology of acute ischemic stroke treatment in neurocritical care (NCC). Consensus was defined a priori by selecting a 6 ("agree") or a 7 ("strongly agree") on a 7-point Likert scale, which was used to gather agreement from a panel of 18 experts in the field of NCC. The completion of three distinct rounds of DELPHI consensus was designated as the study's endpoint. Following the three DELPHI rounds, 93 (77.5%) of the statements achieved consensus, 11 (9.2%) of the statements were eliminated, and 16 (13.3%) of the statements failed to reach the initial concordance [61].

1.3 Significance: 80% of people with relapsing-remitting multiple sclerosis (MS) who do not get treatment move to a phase of permanent impairment accumulation known as secondary progressive MS within 20 years of the disease's inception. Rarely has the relationship between this conversion and disease-modifying therapies (DMTs) been investigated, and never with a definition that has been proven to work.The aim of the study is to ascertain whether the kind, dosage, and timing of disease-modifying therapy use are correlated with a higher risk of developing secondary progressive MS, as defined by a validated diagnosis.Design, environment, and people involved: 68 neurology facilities across 21 countries participated in a prospective cohort study that examined patients with relapsing-remitting MS who started disease-modifying therapies (or clinical monitoring) between 1988 and 2012 and had at least a 4-year follow-up.Exposure include the use, kind, and timing of the disease-modifying therapies fingolimod, natalizumab, alemtuzumab, glatiramer acetate, and interferon beta. 1555 patients were enrolled after propensity-score matching (latest follow-up, February 14, 2017). Principal result and measurement: Transition to secondary progressive MS that is objectively defined. Patient with Multiple Sclerosis outcomes made possible by the digital twin shown in **Fig. 1.5**

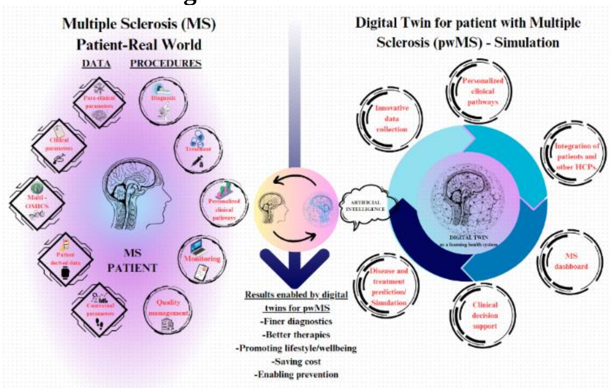


**Fig. 1.5: Shows use of digital twin to improve patient with Multiple Sclerosis in a simple scheme.**

1.4 Conclusions and applicability: Compared to initial treatment with glatiramer acetate or interferon beta, patients with relapsing-remitting MS who received fingolimod, alemtuzumab, or natalizumab had a decreased likelihood of developing secondary progressive MS. These results, when weighed against the hazards associated with these medications, could be useful in guiding disease-modifying therapies selection [62].

Recently, two linked applications-one for the patient and one for the therapist-have been combined to provide a home-based rehabilitation system for stroke survivors (Baptista *et al.*, Comput. Meth. Prog. Biomed. 176:111-120, 2019. Prior trials of the suggested approach were conducted on individuals in good health. However, a clinical investigation that takes stroke survivors into account is required for an impartial assessment. In ten chronic post-stroke spastic patients, the home-based rehabilitation program will be assessed in this study. To do this, each patient uses the home-based rehabilitation system to complete two exercises that simulate upper limb spasticity. Research is done on the effects of the colour-based 3D skeletal feedback that directs patients throughout training. The Time Variable Replacement (TVR)-based average distance, as well as the average postural angle used in Baptista et al. (Comput. Meth. Prog. Biomed. 176:111-120, 2019), are stated to correlate the movement and the posture of the patient with and without showing the feedback proposals, respectively. In addition, three distinct questionnaires created especially for this research are employed to assess the patient's and therapist's user experiences. Overall, the documented results propose the significance of the proposed system for the home-based rehabilitation of stroke survivors [63].

Recent studies on neuroplasticity illustrate how the brain adapts to injury or structural changes (Piai *et al.*, 2020; Hartwigsen and Saur, 2019; Herbet *et al.*, 2016). These studies show that the brain can lively remodel its neuronal circuits to retain functionality

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regardless of major pathology. This takes place through molecular and cellular adaptations, such as the growth of new parts of the nerve cells and the cell's firing strength, which are vital for the recovery or realignment of neurological functions. Emerging evidence indicates that this plasticity goes beyond basic compensation and supports recovery through synaptic growth in injured areas (Pascual-Leone *et al.*, 2005). According to Diniz and Crestani (2023) and Price and Duman (2020), these findings emphasize neuroplasticity as a vital component of brain function that is required for learning and adaptability [64].

***5. Digital twin in diabetes:***

Type 2 diabetes ($T_2DM$) is a disease with an intricate and diverse developmental process, making it a perfect applicant for evaluating the development of biomedical digital twins. The global prevalence of Type 2 diabetes (T2DM) has reached an alarming 537 million, with projections suggesting a staggering increase to over 783 million by the year 2045[66l].The rapid escalation in $T_2DM$ cases is principally ascribed to three critical factors: demographic shifts towards an aging population, rising trends in obesity, and a heightened susceptibility among certain ethnic groups [67].The impact of Type 2 diabetes ($T_2DM$) on health is severe, leading to a substantially higher risk of developing life- threatening complications such as cardiovascular diseases, end-stage renal disease (ESRD), retinopathy, and neuropathy [67].Achieving optimal metabolic control in Type 2 diabetes ($T_2DM$) requires a holistic approach that incorporates both lifestyle modifications and pharmacological interventions to ensure long term effectiveness [67]Previous research on digital interventions, such as the Digital Twin Program, has demonstrated that multifaceted approaches can lead to substantial enhancements in metabolic health outcomes, including improved glycaemic control and decreased medication usage [68-69]. In recent years, several technological interventions have been investigated to optimize Type 2 diabetes management, including Continues Glucose Monitoring, predictive modelling for postprandial glucose responses (PPGRs) based on meal specific food intake and telehealth services [70-72]. The Digital Twin approach marks a significant advancement in Type 2 diabetes ($T_2DM$) management, offering a tailored and comprehensive intervention that acknowledges the intricate complexities of the disease. Unlike other technologies that offer generic solutions, the digital Twin intervention leverages machine learning and the Internet of Things (loT)technology to generate personalized virtual replicas or "twins" of individuals, offering a tailored approach [73,74]. These digital twins support predictive modelling and personalized management of $T_2DM$ by harnessing of broad spectrum of data, including Continues Glucose Monitoring (CGM), precision nutrition, physical activity patterns, sleep quality, and stress management techniques such as deep breathing exercises [68,69,73,74]. The digital twin holds significant potential for managing diabetes on multiple scales, acting as a vital component in the disease management cycle shown in **Fig. 1.6.**

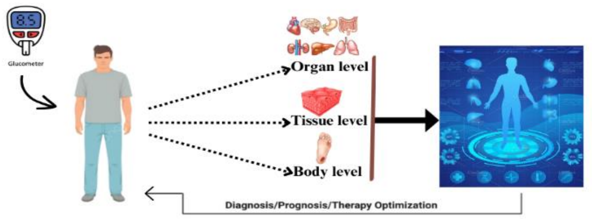


**Fig. 1.6: The application of digital twins in the care of diabetic patients.**

Shamanna *et al.*, [68,75] presented a twin precision treatment (TPT) program in patients with diabetic hypertension, aiming to improve insulin resistance and hypertension management. Thamotharan *et al.*, [76] presented a framework of human digital twin (HDT) and Internet of Things architecture aimed at personalized management of $T_2DM$ in older adults.

Wang S, Han J, Jung SY, Oh TJ, Yao S, Lim S, *et al.*, presented a development and implementation of patient-level predictive models of end stage renal disease in type 2 diabetes patients leveraging fast healthcare interoperability resources for data integration and analysis [77]. Parmesh Shamanna *et al.*, proposed a study on utilizing digital twin technology to deliver precision nutrition and improve glycaemic control, as measured by HbA1c reduction in Type 2 Diabetes patients [75].

***6. Digital twin in surgical training:***

The use of digital twin in the surgical field is to develop a patient model for cross-functional teams to plan a surgery, verify the anatomy and thus minimise the risk of damage to the structures. A number of surgical specialties analysed patient-specific simulation, including neurosurgery, vascular surgery and interventional radiology. As an example, the use of the Digital Twin in treating cardiovascular disease is budding, and there is a growing concern in the application of Artificial Intelligence in vascular surgery [78].

In 2018, the Philips team uses digital twin in medical field; The Philips Heart Navigator tool combines CT images in a single image of the patient's heart anatomy. The characteristic of digital twin provides real-time 3D perception into the positioning of devices during surgery, which can make the earlier planning of the process simpler. Similarly, in 2022 Cydar team used digital twin and they harnessed the latest in cloud GPU computing, computer vision and machine learning technology. It advanced surgical visualization and decision making in theatre, and across the surgical pathway [78].

Up-to-date analysis of studies on soft tissue simulation, surgery simulation, and haptic feedback,

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gives a good summary of related enabling technologies for real-time surgery simulation systems up until 2018. Therefore, we conducted a systematic literature review in the time period from January 2018 to December 2021 following the PRISMA protocol [28]. The objective of this review was to pinpoint the related enabling technologies for a digital twin for arthroscopic knee surgery, and the search was therefore directed towards technical articles [80].The idea of the Digital Twin has been used in Product life cycle Management (PLM), in a previous work at the University of Michigan in 2002.The concept of twin or "Twining" has been used in the field of manufacturing by National Aeronautics and Space Administration (NASA) Apollo project in the late 1960s. in this project, National Aeronautics and Space Administration (NASA) created two perfect copies of space vehicles. One that was left on Earth was known as the twin, which was utilized to mirror the state of the space vehicle that performed the mission [81]. Graphical representation of number of digital twin studies involved in this review in given below **Fig. 1.7.**

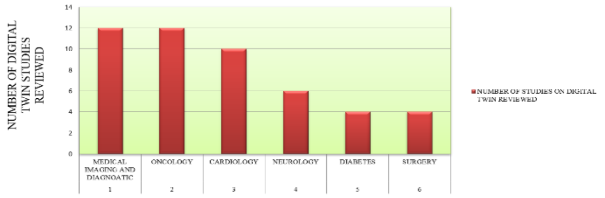


**Fig. 1.7: Graphical representation of number of digital twin studies involved in this review.**

## III. DISCUSSION

The review concludes that the Digital Twin (DT) technology has demonstrated efficiency in treating a range of medical disease, including orthopaedics, surgery, cardiovascular disease, and pharmacy. Digital Twin uses wearable technology or sensor to collect real-time patient health data, enabling continuous monitoring and action. It can be deployed for patient care and hospital management, and it can send medications and treatment plans for validation. However, the effectiveness of DigitalTwin depends on the accuracy of the simulation, and current methods lack individualized assessment and validation. Concerns also exist regarding socio-ethical hazards, which include privacy, legal and economic difficulties, and the possibility of prejudice or meddling with actual individuals. Internet of Things, big data, and Artificial Intelligence (AI) technological developments can enhance disease prediction, real-time monitoring, and prompt lifestyle and preventive advice through DigitalTwin.

## IV. CONCLUSION

In this review, we examined the evolution of Digital Twins (DT) and their applications in healthcare by evaluating numerous studies across various medical fields. We determined that Digital Twin will see broader application in the future to address healthcare challenges such as, dynamic analysis, precise disease treatment and real-time monitoring, which traditional methods fail to adequately address. Any pertinent facilities in the medical environment can have their characteristics and activities stimulated by digital twin technology, creating a link between observable states and the physical entities (PE) of the Digital Twin. Although ethical and technological issues with Digital Twin in healthcare still need urgent attention, the progress is promising. Digital Twin applications in healthcare extend beyond diagnosing and treating diseases to predicting state of health and disease, providing a quantitative comprehension of health and illness. As a pivotal approach in future medicine, digital twin healthcare will enable precision medicine and make personalized treatment a practical reality.

## FUTURE PERSPECTIVES

The count of studies involved in Digital Twin in Field Medicine will enhance the research of Digital Twin and breakthrough in the innovation of the Internet of Things, Big data and Artificial Intelligence. As explained by the Health Market Report, Globel Spending on the Internet of Things in Healthcare field is expected to reach USD 188.2 billion by 2025 with 21.0% growth rate and the reach of national expenditures will be 1795 per capita with 1.50% growth rate since 2012[78]. The potential of Digital Twins is to revolutionize surgical care, research and training. Apart from its Potential, the industry of healthcare is still in its infancy of being able to mapping the body of humans, down to a dynamic real time digital twins [79].

## DIGITAL TWINS CAN REDUCE HEALTHCARE COSTS IN NUMEROUS WAYS

Digital twins can forecast equipment failures, decreasing downtime and stretching the lifespan of medical devices. It can help tailor treatment plans to individual patients, reducing the cost of unnecessary interventions. It can activate remote monitoring, decrease hospitalization costs, and enhance patient convenience. It can aid in distributing resources more efficiently, reducing waste, and improving patient outcomes. It can replicate clinical trials, reducing the cost and time required for new treatment advancements. It can encourage patients to take a more intact role in their care, improving health literacy and reducing costs related to non-adherence. It can help reduce hospital readmissions by identifying high-risk patients and enabling early intervention. It activates personalized treatment plans and related costs. It can help reduce diagnostic costs by identifying the most effective tests

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and procedures. It can help reduce medication costs by identifying the most effective treatment regimens and minimizing adverse reactions. It can improve patient safety by identifying potential safety risks. By using digital twins, patients can benefit from more personalized, efficient, and cost-effective healthcare, leading to improved outcomes and reduced healthcare costs.

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