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A SYSTEMATIC LITERATURE REVIEW ON THE ROLE OF DIGITAL HEALTH TWINS IN PREVENTIVE HEALTHCARE FOR PERSONAL AND CORPORATE WELLBEING

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Abstract

Digital Health Twins (DHTs) represent a groundbreaking advancement in personalized and predictive healthcare, functioning as real-time, data-driven digital replicas of individual patients. By integrating continuous physiological, behavioral, and contextual data from sources such as wearable devices, biosensors, electronic health records (EHRs), and mobile health platforms, DHTs simulate the progression of health conditions, predict outcomes, and enable individualized care planning. This systematic literature review investigates the current landscape of DHT development and implementation with a specific focus on their clinical, technological, ethical, and organizational dimensions. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, ensuring transparency, reproducibility, and methodological rigor. A total of 72 peer-reviewed journal articles published between 2010 and 2022 were selected from five major databases, representing diverse disciplines including biomedical engineering, health informatics, artificial intelligence, and occupational health. The findings indicate that DHTs are being widely utilized for early detection of chronic diseases, personalized risk profiling, and virtual treatment simulations, particularly in specialties such as cardiology, oncology, and neurology. In parallel, DHTs are enabling a new era of personal health management through real-time biofeedback, digital coaching, and self-monitoring tools that empower individuals to make data-informed lifestyle decisions. The review also reveals emerging applications of DHTs in corporate health and workforce wellbeing, where they support occupational health surveillance, wellness program optimization, and predictive modeling of employee engagement and absenteeism. This review not only consolidates current knowledge across multiple sectors but also identifies critical research and policy gaps, highlighting the need for robust ethical frameworks, standardized interoperability protocols, and inclusive governance mechanisms to ensure the equitable and responsible implementation of DHTs across healthcare ecosystems.

Keywords

Digital Health Twins, Preventive Healthcare, Personal Wellbeing, Corporate Health Management, Virtual Health Models;

INTRODUCTION

Digital Health Twins (DHTs) represent a novel convergence of healthcare and digital engineering, defined as real-time, digital replicas of physical human beings that mirror their physiological, behavioral, and medical data to simulate, predict, and optimize health outcomes (Ahmadi-Assalemi et al., 2020). The term "digital twin" originally emerged in the manufacturing sector, where it was used to describe virtual models of physical assets for predictive maintenance and lifecycle management (Ahmadian et al., 2022a; Erol et al., 2020). Its adaptation into healthcare has prompted a radical reimagining of personalized medicine, preventive care, and clinical decision-making (Ahmadian et al., 2022b; Fagherazzi, 2020). Built on data streams from wearable devices, electronic health records (EHRs), biosensors, and machine learning algorithms, DHTs continuously update to reflect changes in an individual's health status, creating a dynamic model that healthcare providers can use to monitor, diagnose, and intervene in real time (Akash & Ferdous, 2022; Sahal et al., 2022). The construction of a DHT relies on the integration of various technological layers, including the Internet of Things (IoT), cloud computing, artificial intelligence (AI), and data analytics (Alaasam et al., 2019). Each of these technologies plays a unique role: IoT captures health metrics, AI processes and predicts outcomes, and cloud infrastructures support scalable data storage and computational needs (Allen et al., 2021; Sharma et al., 2020). Real-time data synchronization is essential for the effectiveness of DHTs, as it ensures fidelity between the physical and virtual entities (Angulo et al., 2020). Moreover, interoperability standards, such as HL7 FHIR and openEHR, are critical for seamless data exchange across platforms and devices (Armeni et al., 2022; Bagaria et al., 2019). This ecosystem allows for a personalized, predictive, and preventive model of healthcare (Aubert et al., 2021; Sharma et al., 2020), which contrasts sharply with traditional reactive approaches (Allen et al., 2021). Across the globe, healthcare systems are increasingly burdened by aging populations, chronic diseases, and escalating medical costs. These challenges have driven the urgent need for more effective and efficient care models, prompting interest in DHTs as a solution to augment healthcare delivery and resource management (Alaasam et al., 2019; Allen et al., 2021). Countries like the United States, Germany, China, and the Netherlands have been early adopters in piloting DHT technologies in both academic and clinical settings (Angulo et al., 2020; Erol et al., 2020). The integration of DHTs into national health strategies has been facilitated by the proliferation of health informatics infrastructure, growing digital literacy among clinicians, and increased investment in health-tech innovation (Armeni et al., 2022; Sahal, Alsamhi, Brown, et al., 2021). Global institutions, including the WHO and the European Commission, have recognized the role of DHTs in improving patient-centered care, particularly through real-time risk prediction and personalized treatment planning (Aubert et al., 2021). In the European Union's Horizon 2020 program, DHTs have been prioritized in several funded projects focusing on cardiovascular, oncology, and mental health applications (Azzaoui et al., 2020; Sharma et al., 2020). Meanwhile, in Asia, countries like Japan and South Korea have emphasized digital twins in public health initiatives, aiming to prevent disease outbreaks and promote aging-in-place through sensor-driven health monitoring systems (Aubert et al., 2021; Rosen et al., 2015). In Africa, mobile health initiatives combined with DHT prototypes are being explored as low-cost alternatives to traditional healthcare in rural areas (Azzaoui et al., 2020).

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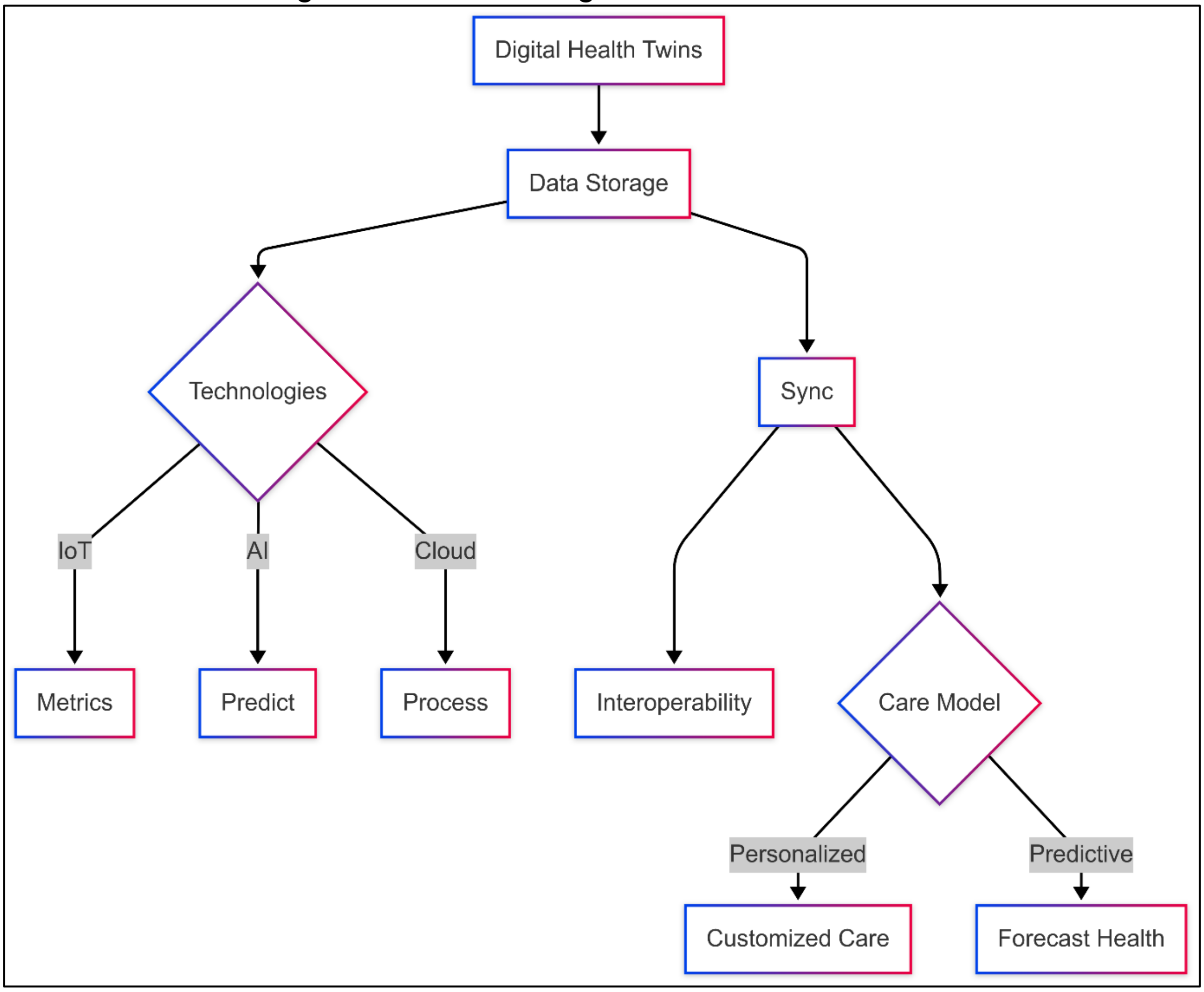
Figure 1: Overview of Digital Health Twin Processes



The international proliferation of DHTs also aligns with the United Nations Sustainable Development Goals, particularly Goal 3, which aims to ensure healthy lives and promote well-being for all at all ages (Badano et al., 2018). This alignment has encouraged cross-sector collaboration between governments, healthcare providers, and technology companies (Bagaria et al., 2019). Large-scale implementation, however, is not without obstacles, such as ethical concerns regarding surveillance and autonomy, which are currently under regulatory review by bioethics committees worldwide (Badano et al., 2018). Nonetheless, the international relevance of DHTs remains high, as their applications span clinical, preventive, and occupational health domains (Bagaria et al., 2019). Preventive healthcare has gained global momentum as the most cost-effective strategy for improving public health and reducing long-term healthcare expenditures (Angulo et al., 2020). In this context, DHTs are increasingly recognized for their role in enabling proactive interventions based on early detection of physiological anomalies and lifestyle patterns (Allen et al., 2021; Angulo et al., 2020). Through continuous data monitoring, DHTs can signal early deviations in biometrics such as heart rate variability, glucose levels, sleep patterns, and blood pressure, which are critical indicators of emerging health risks (Alaasam et al., 2019; Armeni et al., 2022). The use of DHTs in personalized medicine has been particularly prominent in oncology and cardiology. For instance, virtual replicas of cancer patients have been used to simulate tumor growth and test drug responses, enabling oncologists to tailor treatment regimens with improved efficacy (Angulo et al., 2020). Similarly, cardiovascular DHTs are being employed to simulate patient-specific hemodynamics and assess risks of arrhythmias and heart failure (Armeni et al., 2022). These models leverage patient-specific anatomical and functional data derived from imaging techniques like MRI and CT, combined with real-time physiological monitoring (Aubert et al., 2021). The precision afforded by DHTs supports the shift from population-based risk assessments to individualized risk profiling and health planning (Ahmadian et al., 2022b). In chronic disease management, DHTs help maintain continuity of care by alerting healthcare teams to critical fluctuations, supporting remote interventions and medication adherence (Akash & Ferdous, 2022). Digital platforms embedded with behavioral nudges also encourage users to adopt healthier lifestyles, a cornerstone of preventive medicine (Alaasam et al., 2019). As such, the dual capability of DHTs—to monitor and simulate—offers a compelling toolset for advancing both early diagnosis and customized care (Ahmadi-Assalemi et al., 2020).The primary objective of this systematic literature review is to critically analyze and synthesize the current body of research on Digital Health Twins (DHTs) to evaluate their roles in enhancing preventive healthcare at both individual and organizational levels. This objective stems from the growing global interest in shifting from reactive medical interventions to proactive and personalized health strategies enabled by digital innovation. The review seeks to understand how DHTs—defined as dynamic, data-driven virtual models that replicate individual health profiles—are being implemented across various healthcare systems to support early diagnosis, risk prediction, and behavior modification. Furthermore, the study explores the application of DHTs in corporate wellness programs, where employee health data can be used to design targeted interventions that improve workforce performance, reduce absenteeism, and promote long-term organizational productivity. A central research aim is to investigate the interdisciplinary integration of Internet of Things (IoT), artificial intelligence (AI), wearable technology, and cloud computing that underpin DHT architectures, while also examining the challenges associated with data standardization, privacy, and system interoperability. In doing so, the review identifies critical factors that enable or hinder the successful deployment of DHTs in both clinical and occupational health contexts. Additionally, this study categorizes the types of health indicators most commonly modeled in DHTs, ranging from cardiovascular metrics to mental health parameters, and assesses their predictive accuracy in real-world environments. By meeting this objective, the review provides a foundational understanding of how DHTs contribute to personalized, predictive, and preventive healthcare, thereby offering a comprehensive framework for researchers, practitioners, and policymakers engaged in digital health transformation.

LITERATURE REVIEW

The emergence of Digital Health Twins (DHTs) as a transformative innovation in the healthcare ecosystem has led to a proliferation of academic research exploring their applications, design architectures, and implications for preventive healthcare. DHTs—real-time, data-integrated virtual models of human physiology and behavior—are increasingly recognized for their potential to revolutionize clinical diagnostics, enhance personalized medicine, and optimize health management strategies in corporate environments. This literature review section systematically examines the existing scholarly discourse across diverse fields including biomedical engineering, health informatics, artificial intelligence, organizational health, and data ethics. It synthesizes findings from peer-reviewed journal articles, industry reports, and international policy documents to offer a structured understanding of the key themes, technological underpinnings, and multidisciplinary considerations surrounding DHT implementation. To ensure a comprehensive and focused review, the section is divided into clearly defined thematic areas, each addressing a specific aspect of DHT development and application. The literature is categorized to reflect both micro-level applications (e.g., individual health monitoring, disease prediction) and macro-level strategies (e.g., workplace health management, population health surveillance). Particular attention is given to the integration of DHTs with emerging technologies such as AI, IoT, and cloud computing, along with the ethical, legal, and security concerns posed by such integrations. The structure of this literature review is designed to guide readers through a progressive understanding of how DHTs function, what benefits they provide, the barriers to their adoption, and their role in promoting both personal and corporate wellbeing.

Digital Health Twins in Biomedical Research

The concept of Digital Twins (DTs) in healthcare emerged from the foundational ideas of digital replication in engineering systems, evolving into what is now recognized as Digital Health Twins (DHTs)—virtual models of an individual's biological, behavioral, and physiological attributes for real-time health analysis (Dillenseger et al., 2021). The historical development of DHTs can be traced back to NASA's Apollo program, where engineers used mirrored simulations to predict physical system performance under spaceflight conditions (Galli et al., 2021). While the term "digital twin" was formally coined in manufacturing contexts, its adaptation into medicine was driven by parallel advancements in big data, artificial intelligence (AI), and personalized medicine (Iyawa et al., 2016). A DHT is now broadly defined as a dynamic, continuously updating virtual representation of a patient's health, designed to simulate physiological processes and support personalized treatment strategies {Kallas, 2023 #2}. Scholars such as Gillette et al. (2021) and Karkar et al. (2015) emphasized that the operational scope of DHTs goes beyond visualization to include decision support, predictive modeling, and feedback mechanisms for clinicians and patients.

Digital Health Twins rely on integrating diverse datasets, including electronic health records (EHRs), wearable device outputs, genomic profiles, and lifestyle data (Fagherazzi, 2020). They are increasingly being leveraged to offer a proactive approach to managing chronic diseases and detecting early health anomalies (Semakova & Zvartau, 2018). The shift toward data-driven preventive health has reinforced the importance of real-time monitoring and virtual simulation, positioning DHTs as a core tool in modern health informatics (Bagaria et al., 2019). Although still a relatively novel construct within healthcare systems, DHTs now stand as a critical component in personalized and predictive medicine research, supported by multidisciplinary contributions from biomedicine, systems engineering, and data science (Bielefeldt et al., 2015).

The transition of digital twin technology from manufacturing to healthcare represents a significant interdisciplinary crossover that has reshaped biomedical innovation. In the manufacturing sector, digital twins were first conceptualized as virtual models used for simulating, testing, and optimizing physical products or systems in real-time environments (Canedo, 2016; Hose et al., 2019). This method was instrumental in predictive maintenance, lifecycle management, and failure analysis of industrial equipment, laying the foundation for the development of analogous models in healthcare (Bielefeldt et al., 2015). As AI, cyber-physical systems, and IoT technologies matured, their capabilities were adapted for modeling human biological systems, giving rise to Digital Health Twins (Hose et al., 2019; Sahal, Alsamhi, Brown, et al., 2021).These healthcare applications involve significantly greater complexity due to the variability in human physiology and the multifactorial nature of health outcomes (Azzaoui et al., 2020).

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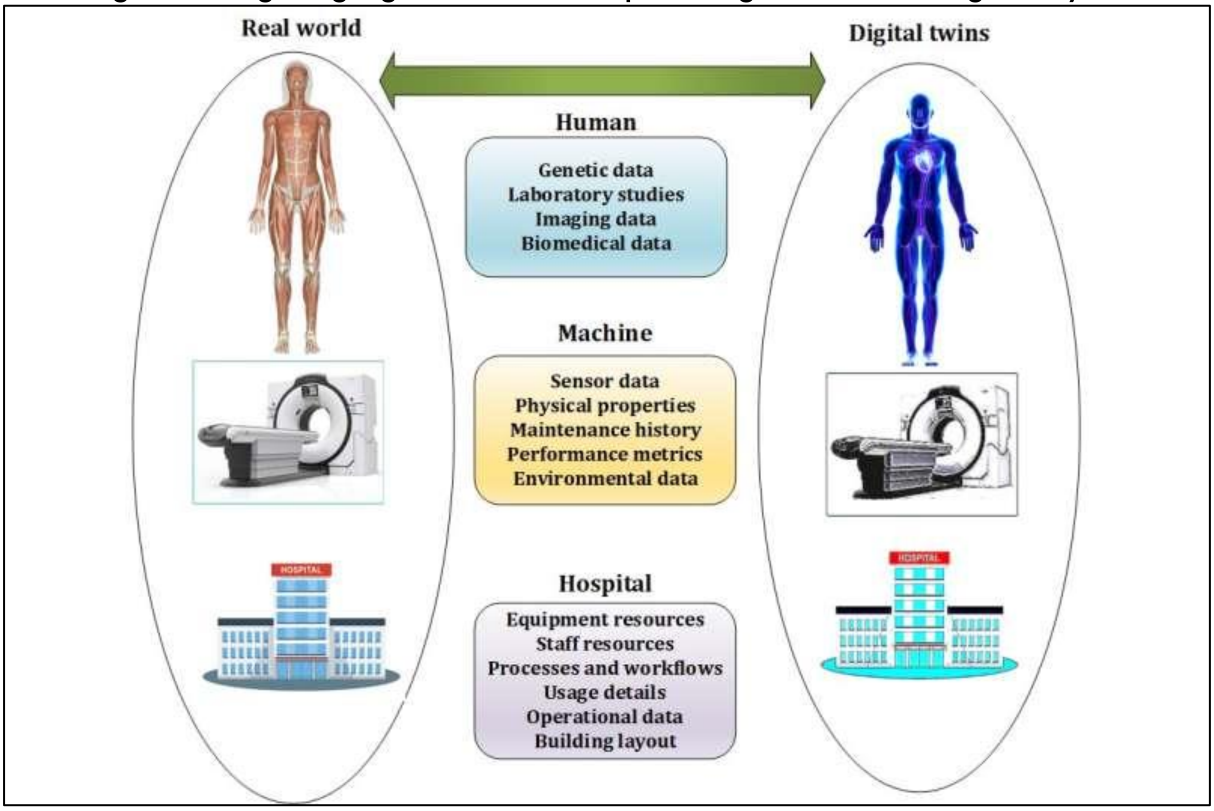
Figure 2: Integrating digital twins and deep learning for medical image analysis



Source: medicalxpress.com (2022)

Several scholars argue that the evolution of DHTs has been driven by the rising demand for individualized healthcare solutions, enabled by precision medicine and real-time health data collection (Sahal et al., 2022). Biomedical researchers adopted simulation models from the industrial domain to represent organs, physiological functions, and patient-specific conditions, enabling more accurate clinical predictions and treatment planning (Hasan et al., 2020). For instance, cardiovascular digital twins simulate hemodynamic parameters using the same digital thread logic applied in automotive crash simulations (Hasselgren et al., 2021). Similarly, oncology research has leveraged digital twins to test chemotherapy responsiveness in virtual environments before initiating clinical interventions (Yaqoob et al., 2020). This translational leap from mechanical twins to biological counterparts was facilitated by the integration of health informatics systems, such as EHRs and sensor networks, forming a feedback-rich environment for modeling real-time physiological changes (Akash & Ferdous, 2022).

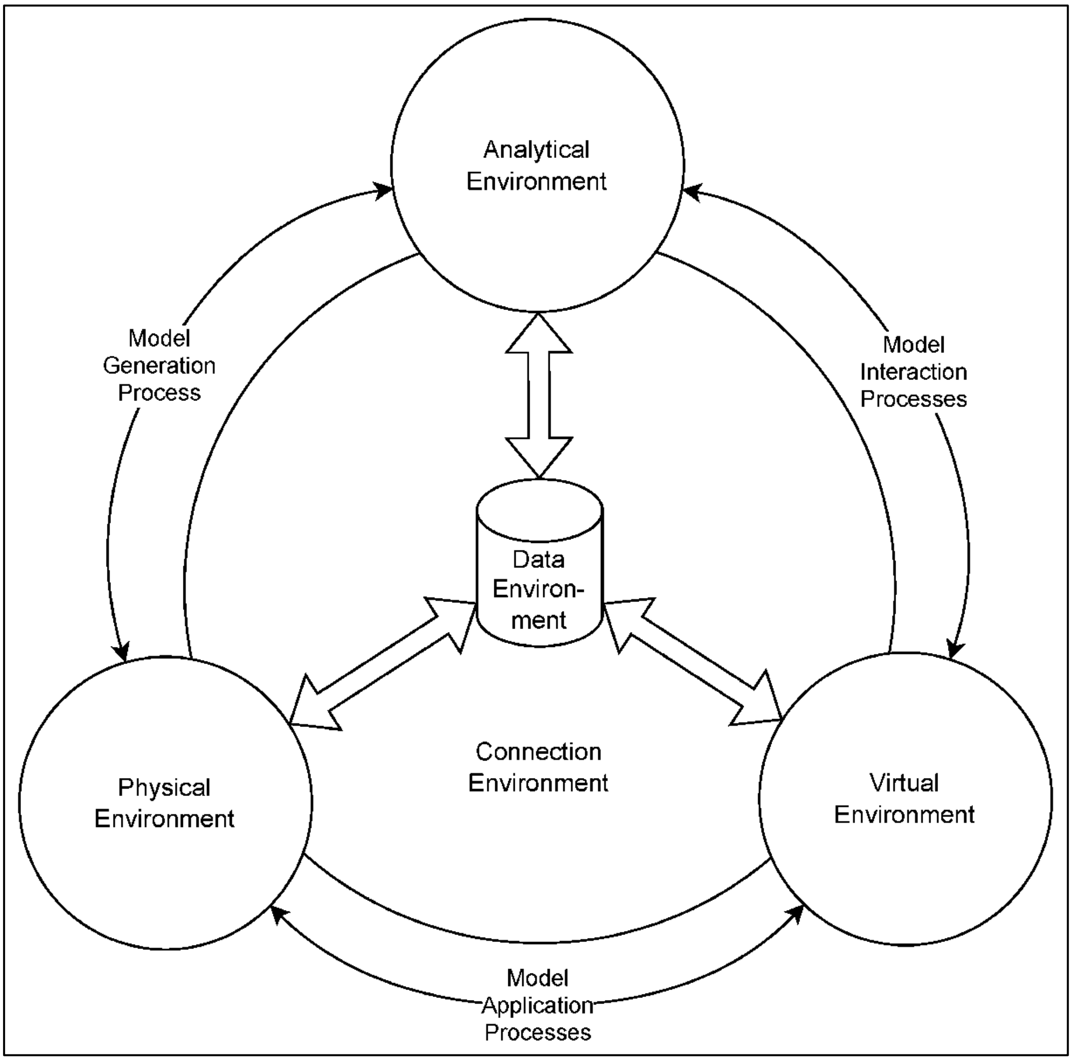
The development and implementation of Digital Health Twins are grounded in foundational frameworks that facilitate modeling, simulation, and real-time synchronization of human health data. One of the most prominent frameworks is the "digital thread" architecture, which enables continuous data exchange between physical health entities and their virtual counterparts through interoperable platforms (Akash & Ferdous, 2022; Sahal, Alsamhi, Brown, et al., 2021). In academic research, this approach has been extended using the Systems Biology Markup Language (SBML) and standardized health data formats such as HL7 FHIR and openEHR to ensure semantic interoperability and modular scalability across DHT platforms (Canedo, 2016). The digital twin framework developed by Azzaoui et al. (2020) for cardiac health integrates 3D modeling, electro-mechanical simulations, and personalized biometric inputs to create individualized risk profiles for cardiovascular disease.

Industry-led frameworks, such as Siemens' Healthineers Digital Twin platform and Dassault Systèmes' 3DEXPERIENCE virtual human modeling, have similarly incorporated patient-specific anatomical and physiological parameters into real-time simulation engines (Sahal et al., 2022). These systems emphasize modularity, enabling the creation of organ-specific or system-wide twins that can be used for diagnostic, therapeutic, or preventive purposes. Integration with AI modules enhances their predictive accuracy and decision-support capabilities, particularly in high-risk areas like cancer therapy and neurology (Hasselgren et al., 2021; Sahal et al., 2022). From a computational perspective, foundational DHT frameworks emphasize closed-loop systems, where real-time feedback from the patient is used to update simulation parameters, thereby increasing the model's clinical relevance (Yaqoob et al., 2020). Theoretical models such as the "Living Lab" approach also support iterative user-centered development of DHTs through co-design between patients, clinicians, and developers (Akash & Ferdous, 2022). These participatory frameworks have informed several academic pilot studies across Europe and North America, particularly in projects funded under the EU Horizon 2020 program (Fagherazzi, 2020). Academic institutions such as Stanford, Johns Hopkins, and ETH Zurich have advanced these frameworks by embedding simulation-based medical training and research into interdisciplinary programs (Sahal et al., 2022). Collectively, these foundational models provide the architectural and methodological backbone necessary to standardize DHT implementation across varied clinical and research contexts.

Technological Infrastructure Underpinning Digital Health Twins

Digital Health Twins (DHTs) are constructed on a technological infrastructure that integrates artificial intelligence (AI), the Internet of Things (IoT), big data analytics, and cloud computing to deliver real-time, predictive, and interactive simulations of human health. The convergence of these technologies enables the creation of complex, dynamic virtual representations of individuals that continuously evolve in response to new data inputs (Hasan et al., 2020; Rahaman & Islam, 2021). AI is central to the functioning of DHTs, as it facilitates pattern recognition, anomaly detection, and clinical decision support through machine learning and deep learning algorithms trained on large datasets (Ahmed et al., 2022; Azzaoui et al., 2020; Hasan et al., 2020). The incorporation of IoT devices, including smartwatches, fitness trackers, and implantable sensors, allows for constant health data acquisition, which feeds into AI models for analysis and simulation (Akash & Ferdous, 2022; Aklima et al., 2022; Yaqoob et al., 2020). Big data analytics processes the enormous volume of real-time health data by organizing, filtering, and extracting actionable insights, which are critical for the accuracy and personalization of DHTs (Humaun et al., 2022; Rahman et al., 2019). Cloud computing provides the computational backbone, offering scalable storage and processing capabilities needed to operate continuous data streams and real-time simulation models (Mahfuj et al., 2022; Park et al., 2021). The seamless interaction between these layers forms a robust digital ecosystem that allows for on-demand access, rapid processing, and adaptive learning. Studies by Lamata (2020) and Bhattad and Jain (2020) demonstrated how these technologies have been effectively deployed in cardiovascular and neurodegenerative disease modeling. Additionally, healthcare systems leveraging these architectures benefit from enhanced diagnostic precision and timely interventions, as shown in pilot implementations in Europe and Asia (Mohiul et al., 2022; Sharma et al., 2020; Yaqoob et al., 2020). These developments collectively reflect how DHTs are grounded in sophisticated, multi-technology platforms that replicate the complexity and variability of human biology in virtual form (Bhattad & Jain, 2020; Park et al., 2021; Sohel et al., 2022).

Figure 3: Components of a Digital Twin.



Source: Grübel et al. (2022).

The role of data acquisition technologies such as electronic health records (EHRs), wearable devices, and biosensors is pivotal in feeding DHTs with accurate, diverse, and continuous health information. EHRs serve as structured repositories of longitudinal clinical data, including demographics, lab test results, medication history, imaging data, and physician notes, which are essential for constructing a comprehensive baseline model of an individual's health (Antonelli et al., 2019; Wu, Lorenzo, et al., 2022). EHR integration enables DHTs to simulate disease progression and predict treatment responses by comparing real-time health parameters against historical benchmarks (Gagne et al., 2014; Lee et al., 2021; Tonoy, 2022). Wearable devices, such as smartwatches and activity trackers, expand the data input landscape by capturing continuous physiological metrics like heart rate, step count, oxygen saturation, and sleep quality (Camps et al., 2021; Corsini et al., 2018; Younus, 2022). These data streams offer a granular understanding of daily fluctuations in health behaviors and conditions, enhancing the temporal resolution of DHT models. Biosensors embedded in clothing or skin patches contribute to non-invasive real-time monitoring of glucose levels, cortisol, sweat composition, and body temperature (Lee et al., 2021). Integration of such devices with mobile apps and cloud platforms allows for automatic uploading and synchronization with centralized DHT engines (Gagne et al., 2014). The synergistic use of EHRs and real-time sensor data contributes to a feedback-rich environment where the digital twin evolves alongside its physical counterpart, improving predictive accuracy and responsiveness (Corsini et al., 2018). (Sahal, Alsamhi, Breslin, et al., 2021)confirmed that such multimodal data integration enhances patient engagement, as individuals can visualize and interact with their health profile in real time. These technologies not only support dynamic health modeling but also establish the foundational interface between the physical human and their virtual representation in a clinically meaningful manner (Shaker et al., 2021). Real-time data synchronization is a defining characteristic of functional DHTs, enabling the continuous updating of the digital model in response to physiological changes in the individual. The synchronization process ensures that the virtual twin accurately mirrors the physical state of the patient by assimilating new data inputs from EHRs, wearables, and biosensors with minimal latency (Vernon et al., 2017). This process is facilitated by high-frequency data pipelines and secure data transmission protocols that enable near-instant communication between edge devices and cloud-based processing engines (Shaker et al., 2021). Real-time updates allow DHTs to simulate disease states and forecast health outcomes with high temporal fidelity, an advantage that static models lack (Antonelli et al., 2019). Simulation models embedded within DHT platforms use mathematical and computational methods, such as finite element modeling, physiological equations, and multi-scale systems biology, to reproduce organ functions, metabolic processes, and biomechanical behavior (Shaker et al., 2021). Feedback loops are implemented to enable continuous recalibration of the model based on deviations between predicted and observed data, thereby improving learning accuracy over time (Brovkova et al., 2021). Clinical studies have demonstrated that the inclusion of feedback mechanisms enhances diagnostic reliability and supports tailored therapeutic recommendations (Hirschvogel et al., 2019). For example, a cardiovascular DHT can adjust its simulated output in response to new blood pressure readings, thereby reflecting an accurate hemodynamic profile for treatment planning (Sahal, Alsamhi, Breslin, et al., 2021). Furthermore, closed-loop feedback systems have been shown to improve adherence in remote monitoring scenarios by sending behavioral nudges and alerts to both patients and clinicians (McMenamin et al., 2018). These interactions between real-time data, simulation, and feedback constitute the core operating mechanism of DHT platforms, reflecting their status as living digital systems that evolve in synchrony with human physiology.

Clinical Applications of DHTs in Preventive Healthcare

Digital Health Twins (DHTs) have emerged as powerful tools in the early detection and risk profiling of chronic diseases through their continuous data acquisition, integration, and analysis capabilities. Unlike static diagnostic models, DHTs enable dynamic, real-time tracking of physiological and behavioral changes, offering personalized insights into disease trajectories long before clinical symptoms manifest (Sahal, Alsamhi, Breslin, et al., 2021). The use of machine learning algorithms to process data from wearable devices, electronic health records (EHRs), and biosensors allows these systems to detect early deviations from individual health baselines, which can serve as precursors to conditions such as hypertension, diabetes, and respiratory illnesses (Antonelli et al., 2019). Personalized risk profiling is a central feature of DHTs, where AI-driven models generate tailored health assessments based on a person's genetic, environmental, and behavioral data (Antonelli et al., 2019; Shengli, 2021). This individualized profiling provides actionable insights into susceptibility to lifestyle-related diseases, enabling proactive management strategies (Le et al., 2021). (Antonelli et al., 2019) demonstrate that continuous integration of physiological metrics, such as blood glucose variability and heart rate patterns, significantly enhances early detection of metabolic and cardiovascular disorders. The predictive capability of DHTs has also been validated in clinical pilots, where patients monitored via DHT platforms showed earlier diagnoses and better health outcomes compared to those receiving conventional care (Corsini et al., 2018; Le et al., 2021). By combining longitudinal health data with advanced modeling techniques, DHTs bridge the gap between prevention and intervention, marking a paradigm shift in chronic disease management (Sahal, Alsamhi, Breslin, et al., 2021).

Clinical applications of DHTs are particularly advanced in fields such as oncology, cardiology, and neurology, where simulation-based decision-making is critical for patient-specific care. In oncology, digital twins replicate tumor growth, predict metastasis patterns, and test virtual responses to chemotherapeutic agents, enabling oncologists to evaluate treatment efficacy without exposing patients to adverse side effects (Vernon et al., 2017). These models leverage genomic, histological, and imaging data to construct high-resolution digital avatars of tumors that simulate their biological behavior in silico (Collins & Varmus, 2015). In cardiology, DHTs have been deployed to simulate heart function under various stress conditions, monitor cardiac electrophysiology, and anticipate complications such as arrhythmias or heart failure based on personalized physiological inputs (Mittelstadt, 2021). Cardiovascular twins are informed by echocardiography, MRI, and electrocardiogram data, which allow for the modeling of myocardial strain, ejection fractions, and valvular functions in real time (Wu, Jarrett, et al., 2022). In neurology, DHTs are being developed to monitor neural signals, predict cognitive decline, and support therapeutic decisions in neurodegenerative diseases such as Alzheimer's and Parkinson's. These applications incorporate electroencephalography (EEG), brain imaging, and behavioral assessments into dynamic neural network simulations capable of tracking progression and testing intervention strategies. The integration of DHTs in these domains has been shown to improve diagnosis precision and enable clinicians to identify optimal therapeutic pathways based on the evolving digital profile of each patient (Figtree et al., 2021). Such applications demonstrate the versatility of DHTs across multiple high-impact medical specialties where accurate modeling and timely intervention can significantly alter disease outcomes (Saeed et al., 2011).

The use of Digital Health Twins in predictive modeling and treatment simulations represents a breakthrough in personalized healthcare by enabling clinicians to virtually test and optimize interventions before applying them in real-world scenarios. Predictive models in DHTs are trained on large, multi-dimensional datasets and incorporate probabilistic algorithms to forecast disease progression, identify critical intervention windows, and simulate therapeutic outcomes (Li et al., 2020). For example, cardiovascular DHTs can simulate the effects of medications on blood pressure and heart rhythm, allowing physicians to explore alternative treatment paths in silico without endangering patient safety (Figtree et al., 2021). Similarly, in oncology, treatment simulations enable oncologists to assess tumor response to different drug combinations or radiotherapy intensities, thereby reducing trial-and-error in clinical protocols (Croatti et al., 2020). These simulations are based on patient-specific biological and environmental factors, which enhance the precision of predictive modeling compared to traditional statistical tools (Masison et al., 2021). Real-time synchronization between simulated predictions and actual patient data feeds continuous feedback into the twin, allowing it to refine its output over time (Martinez-

Velazquez et al., 2019). Predictive modeling is also being applied in behavioral health, where DHTs analyze mood, sleep, and activity data to forecast episodes of anxiety or depression, guiding early behavioral interventions (Li et al., 2020). Wu, Jarrett, et al., (2022) highlight that DHT-based treatment simulations have led to significant reductions in adverse events and improved patient adherence in both pilot and clinical settings. Through advanced modeling, DHTs provide a risk-free environment for medical experimentation that enhances clinical decision-making and supports the broader goals of precision and preventive healthcare (S et al., 2016).

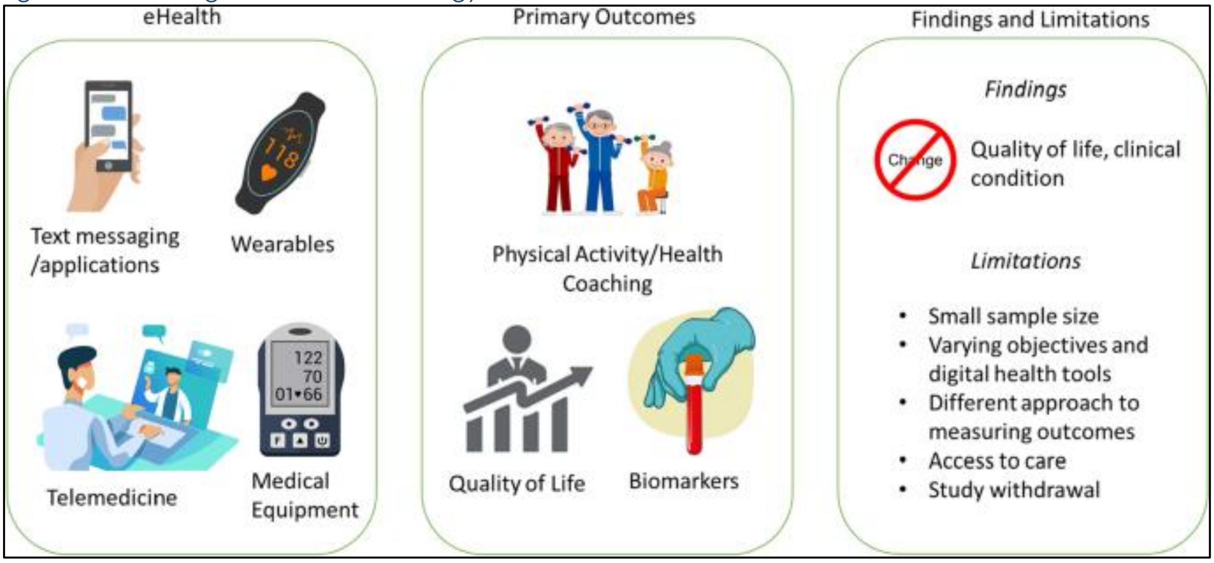
DHTs in Personal Health Management and Self-Monitoring

Digital Health Twins (DHTs) have significantly influenced personal health management by enabling real-time health behavior monitoring and mobile health (mHealth) integration. These platforms continuously track individual physiological, psychological, and behavioral data through wearable sensors, smart devices, and mobile applications, forming an interactive feedback loop between the user and the digital twin (Douthwaite et al., 2021). By linking DHT systems to mobile platforms, individuals gain access to their dynamic health profiles, fostering informed decision-making regarding physical activity, diet, sleep, and mental well-being (Saeed et al., 2011). Mobile health tools such as Apple HealthKit, Google Fit, and MyFitnessPal are increasingly being integrated with DHT frameworks to centralize health data streams and improve personal analytics (Mittelstadt, 2021; Saeed et al., 2011). Through AI-driven analytics, DHTs identify deviations from individual baselines and generate timely alerts, which enhance self-awareness and facilitate behavioral correction (Collins & Varmus, 2015; Strathmann, 2015). Studies show that users who engage with DHT-integrated apps demonstrate improved adherence to health goals, such as physical activity targets and sleep hygiene practices (Douthwaite et al., 2021; S et al., 2016). Furthermore, behavioral interventions based on real-time DHT feedback have outperformed traditional health education models by personalizing motivational strategies and reducing the lag between behavior and response (Naplekov et al., 2018). These systems not only serve as passive monitoring tools but also foster active user participation in health maintenance, which is essential for chronic disease prevention and early-stage intervention (Martinez-Velazquez et al., 2019). The integration of DHTs with mobile health platforms thus constitutes a user-centered model that empowers individuals through timely, actionable, and personalized health insights derived from their continuously evolving digital replicas (Li et al., 2020).

Biofeedback systems and virtual coaching functionalities embedded within Digital Health Twins contribute to behavior modification and lifestyle optimization through responsive, real-time interaction. Biofeedback systems within DHTs collect and analyze data on physiological signals such as heart rate variability, skin conductance, respiration rate, and muscle activity to provide users with immediate insights into their physical or emotional states (Glaessgen & Stargel, 2012). These systems support self-regulation strategies by helping individuals recognize and manage stress, fatigue, or poor posture, especially in occupational and rehabilitative settings (Sun et al., 2022). When linked with virtual coaching modules, DHTs offer personalized recommendations, motivational prompts, and lifestyle guidance based on real-time health patterns and risk factors (Tao et al., 2019). Studies indicate that virtual coaching via DHT platforms improves user engagement and self-efficacy in managing conditions such as obesity, hypertension, and anxiety disorders (Ahmadian et al., 2022a). These coaches often employ AI-powered conversational agents or digital avatars capable of delivering human-like feedback and adaptive goal-setting strategies (Erol et al., 2020; Iyawa et al., 2016). Research by Sun et al. (2022) and

Ahmadian et al. (2022) demonstrates that the integration of behavior-change techniques—such as goal tracking, reinforcement, and self-monitoring—within DHTs enhances long-term adherence to exercise and nutritional plans. Biofeedback and virtual coaching systems are also proving effective in post-operative recovery and rehabilitation, where tailored exercises and rest patterns are adjusted dynamically based on bio-sensor input (Erol et al., 2020; Subramanian, 2020). In this capacity, DHTs not only offer observational insights but also serve as intervention facilitators, translating raw data into behaviorally relevant guidance that aligns with evidence-based lifestyle medicine principles (Tao et al., 2019). These interactive functionalities significantly augment the preventive capacity of DHTs by influencing health behavior in real time, leading to measurable improvements in patient-reported outcomes and quality of life (Subramanian, 2020).

Figure 4: Use of Digital Health Technology in Heart Failure and Diabetes:



Source: Penn et al. (2012)

Remote health monitoring for aging populations and individuals with chronic conditions represents one of the most critical applications of Digital Health Twins, particularly as global demographics shift toward older populations with increased care needs. DHTs facilitate continuous and unobtrusive tracking of vital signs, mobility, cognition, and medication adherence, thereby enabling early identification of clinical deterioration in vulnerable individuals (Camps et al., 2021). Wearable sensors and smart home devices form the hardware backbone of these applications, transmitting real-time data to cloud-based DHT systems that interpret deviations from normal baselines and alert caregivers or medical professionals accordingly (Hirschvogel et al., 2019). In geriatric care, digital twins are employed to detect early signs of frailty, falls, or cognitive decline using gait analysis, sleep pattern monitoring, and ambient sensing (Sahal, Alsamhi, Breslin, et al., 2021). For chronic conditions such as diabetes, heart failure, or chronic obstructive pulmonary disease (COPD), DHTs provide adaptive monitoring frameworks that adjust surveillance intensity and treatment guidance based on current physiological and environmental data (Shaker et al., 2021). Clinical studies have shown that DHT-supported remote monitoring reduces hospital readmissions and improves disease management outcomes by promoting early intervention (Piplani et al., 2021). In residential and long-term care facilities, DHTs contribute to staff efficiency by automating routine health checks and providing decision support for personalized care plans (McMenamin et al., 2018). The utility of DHTs in chronic care is further enhanced through integration with digital medication management systems, ensuring dose accuracy and reducing the likelihood of drug interactions (Dopazo et al., 2021). These platforms also enable family members and caregivers to remotely monitor the health status of elderly or chronically ill individuals, enhancing care coordination without the need for constant in-person supervision (Camps et al., 2021). Through these capabilities, DHTs provide a comprehensive digital infrastructure for aging-in-place and chronic condition management, offering a scalable solution to contemporary healthcare challenges in both urban and rural contexts (Hirschvogel et al., 2019).

Integration of DHTs in Corporate Health and Workforce Wellbeing

Digital Health Twins (DHTs) are increasingly being adopted in occupational health surveillance frameworks to monitor and enhance employee wellbeing while mitigating workplace health risks. By leveraging physiological, behavioral, and environmental data streams from wearable devices, biosensors, and employee health records, DHTs allow organizations to develop comprehensive health profiles for their workforce (Canedo, 2016). These digital profiles enable continuous tracking of occupational health metrics such as stress levels, fatigue, cardiovascular health, and ergonomics, offering real-time insights into employees' physical and mental states (Sahal, Alsamhi, Brown, et al., 2021). DHTs facilitate early detection of work-related health conditions like repetitive strain injuries, burnout, and hypertension, enabling proactive interventions that reduce absenteeism and long-term disability risks (Azzaoui et al., 2020). Occupational applications are especially prominent in high-risk industries such as manufacturing, construction, and healthcare, where real-time data from DHTs are used to alert supervisors of health anomalies or environmental hazards (Sahal et al., 2022). Integration of AI and predictive analytics further enables simulations of exposure scenarios and workforce vulnerability modeling, thus supporting decision-making related to shift design, workload balancing, and emergency response (Hasan et al., 2020). Case studies from Europe and North America have demonstrated that DHTs enhance occupational health compliance by automating health audits and ensuring alignment with regulatory standards such as OSHA and ISO 45001 (Hasselgren et al., 2021). These systems are also increasingly aligned with organizational ESG (Environmental, Social, and Governance) goals, reflecting a broader shift toward sustainable and human-centered corporate health strategies (Azzaoui et al., 2020; Hasselgren et al., 2021). Thus, the application of DHTs in occupational health surveillance serves as a scalable, data-driven approach to fostering workplace safety, productivity, and resilience (Yaqoob et al., 2020).

Digital Health Twins also enhance workforce management by enabling predictive modeling of employee engagement and absenteeism, thereby helping organizations proactively address productivity-related challenges. Predictive analytics embedded within DHT platforms utilize behavioral data, biometric trends, and contextual information to identify early warning signs of disengagement, burnout, or health-related absenteeism (Bagaria et al., 2019; Bielefeldt et al., 2015). These indicators may include irregular sleep patterns, increased resting heart rate, reduced physical activity, or frequent log-in and log-out fluctuations detected via integrated work tools and wearable devices (Sahal, Alsamhi, Brown, et al., 2021). By continuously analyzing such variables, DHTs generate real-time alerts and engagement scores that enable managers and HR professionals to implement timely interventions, such as workload adjustments, mental health support, or wellness coaching (Azzaoui et al., 2020; Sahal et al., 2022). Several corporate pilots have demonstrated that this data-driven approach reduces unplanned absenteeism and improves employee satisfaction, especially when combined with flexible scheduling and hybrid work arrangements

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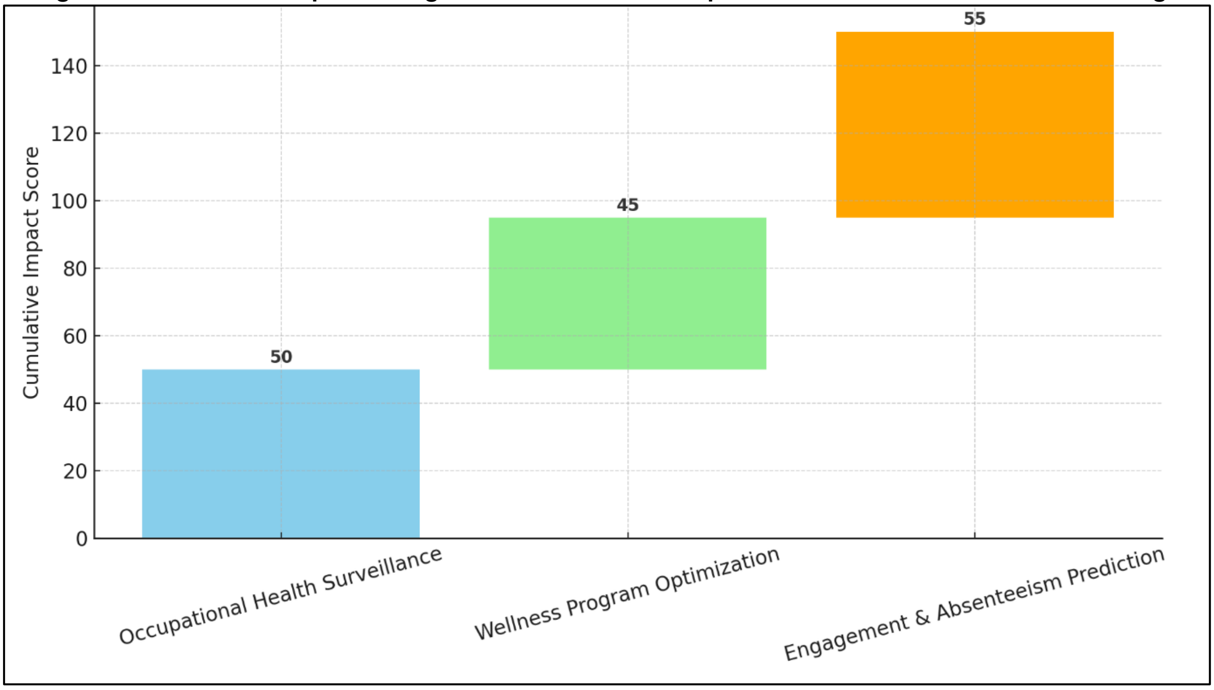
(Hasselgren et al., 2021; Yaqoob et al., 2020). Moreover, these models provide leadership teams with predictive dashboards that track engagement trends at departmental and organizational levels, allowing for data-informed policy development and cultural initiatives (Akash & Ferdous, 2022; Hasan et al., 2020). The use of anonymized aggregate data ensures privacy while maintaining statistical robustness in pattern recognition and forecasting (Rahman et al., 2019). Additionally, DHT-based engagement platforms offer self-service portals for employees to track their own health metrics and engagement scores, thereby fostering a culture of accountability and self-care (Park et al., 2021). Studies from multinational corporations show that organizations that adopt DHTs for engagement analytics experience improvements in employee morale, productivity, and team cohesion (Bhattad & Jain, 2020). Through the convergence of health data and behavioral analytics, DHTs provide an empirical foundation for optimizing human capital management in modern workplaces (Canedo, 2016).

Figure 5: Cumulative Impact of Digital Health Twins on Corporate Health and Workforce Wellbeing



GDPR compliance, HIPAA frameworks, and ethical AI

The implementation of Digital Health Twins (DHTs) necessitates strict adherence to international data protection regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA), both of which govern the ethical management of personal health information. GDPR, enforced across the European Union, emphasizes data minimization, purpose limitation, and user control over personal data, all of which are challenged by the continuous and extensive data processing inherent in DHT platforms (Schroeder et al., 2016). Under GDPR, health data are categorized as "special category" information requiring heightened protections, and the real-time, multi-source integration of such data by DHTs must align with transparency and accountability principles (Erol et al., 2020; Schroeder et al., 2016). HIPAA, which governs the privacy and security of health data in the U.S., sets standards for data de-identification, secure transmission, and patient access rights, yet it was designed primarily for static datasets rather than dynamic digital ecosystems like DHTs (Coppinger, 2016; Dillenseger et al., 2021). Scholars argue that HIPAA's limited scope regarding secondary data use and cross-platform data sharing presents critical

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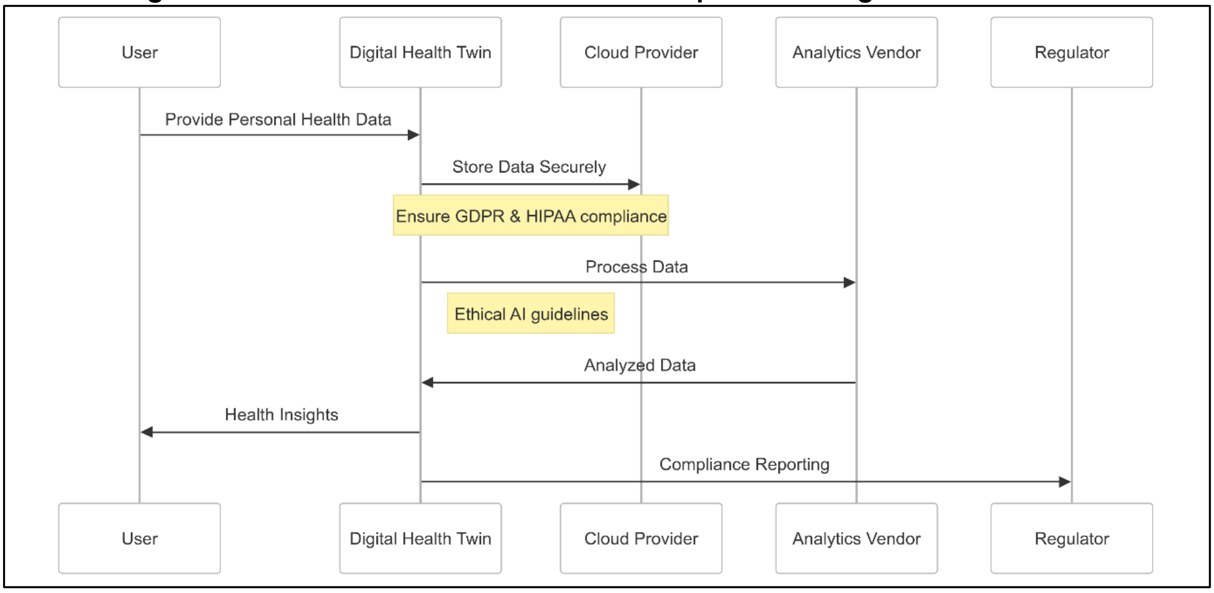
challenges for DHT developers and healthcare organizations (Bagaria et al., 2019). Moreover, the real-time nature of DHTs often involves third-party cloud providers and analytics vendors, creating complex data stewardship scenarios that complicate legal compliance (Aubert et al., 2021). Researchers have emphasized the need for adaptive governance models that accommodate the evolving technical and ethical realities of DHTs without undermining user privacy (Fagherazzi, 2020). Initiatives like the European Health Data Space (EHDS) and the U.S. ONC's Interoperability Rule are steps toward more holistic regulatory frameworks, yet gaps remain in reconciling global standards with DHT operational requirements (Bagaria et al., 2019). Consequently, compliance with GDPR and HIPAA is a foundational but complex undertaking that requires continuous legal-technical alignment to safeguard individual rights within DHT ecosystems (Erol et al., 2020).

Figure 6: Workflow for GDPR and HIPAA Compliance in Digital Health Twins



Ethical concerns surrounding Digital Health Twins extend beyond regulatory compliance and delve into core issues of autonomy, informed consent, and fairness in algorithmic decision-making. The vast data collection capabilities of DHTs raise questions about whether individuals can fully understand and consent to the scope and use of their health data, especially when algorithms continuously update models and generate novel inferences beyond the originally stated purposes (Coppinger, 2016). Scholars highlight the challenge of achieving "dynamic consent" in DHT environments where real-time data streaming and analytics complicate conventional consent mechanisms (Fagherazzi, 2020). Informed consent in DHTs must therefore be iterative, transparent, and accessible to individuals of varying digital literacy levels (Semakova & Zvartau, 2018). Furthermore, the automation of health predictions and risk assessments via AI models in DHTs raises concerns about patient autonomy, particularly when clinical decisions are influenced by opaque algorithms without adequate human oversight (Bagaria et al., 2019). Critics argue that the use of black-box models in DHTs may undermine trust and agency, especially in high-stakes scenarios such as chronic disease treatment or mental health management (Bielefeldt et al., 2015). Ethical AI frameworks have been proposed to address these concerns, emphasizing explainability, accountability, and non-discrimination in predictive modeling (Canedo, 2016). However, implementation remains uneven across platforms and jurisdictions. Studies have found that biased training data, lack of model interpretability, and insufficient user representation in DHT algorithm

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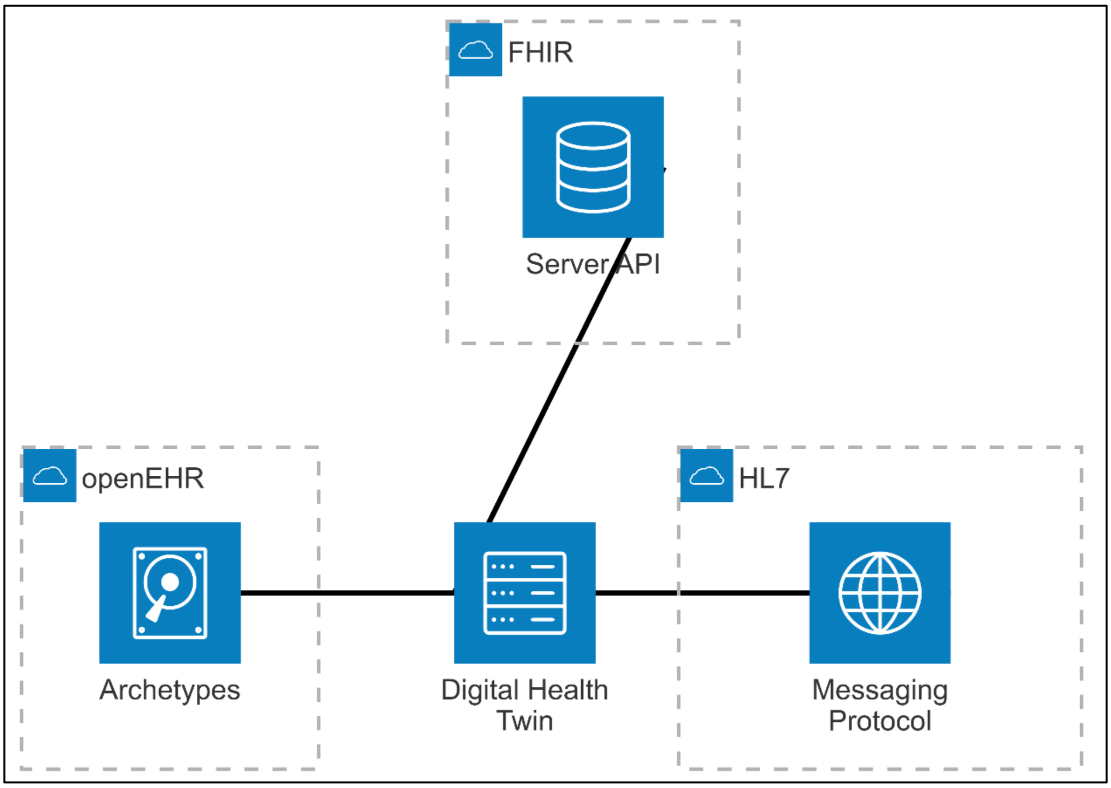
development contribute to disparate health outcomes among marginalized populations (Hose et al., 2019). As DHTs increasingly inform clinical and personal decision-making, embedding ethical AI principles into their design and governance structures is essential for preserving autonomy and equity in digital health environments (Semakova & Zvartau, 2018).

FHIR, HL7, and openEHR standards in DHT implementation

Standardization through interoperability frameworks such as HL7, FHIR, and openEHR is fundamental to the implementation and scalability of Digital Health Twins (DHTs), particularly in enabling seamless data exchange across heterogeneous health information systems. Health Level Seven (HL7) has long served as the backbone of healthcare data communication by offering a set of structured messaging protocols designed to facilitate the exchange, integration, and retrieval of clinical data across diverse systems (Bielefeldt et al., 2015). Its newer specification, Fast Healthcare Interoperability Resources (FHIR), was developed to modernize and streamline health information sharing using web-based standards such as RESTful APIs and JSON/XML formats (Canedo, 2016). FHIR supports real-time data exchange and modular resource definitions, making it highly adaptable for the dynamic data environments that characterize DHT ecosystems (Hose et al., 2019). FHIR's granular data modeling is especially beneficial for DHTs that require continuous updates from wearable devices, biosensors, and electronic health records (EHRs) (Sahal, Alsamhi, Brown, et al., 2021).

Figure 7: Integration of HL7, FHIR, and openEHR with a Digital Health Twin Platform



Furthermore, FHIR's compatibility with mobile health apps and remote monitoring systems has made it a critical enabler of real-time synchronization and decision support within patient-centric digital twin platforms (Azzaoui et al., 2020). Sahal et al., (2022) have underscored the role of FHIR in facilitating AI-driven analytics pipelines by providing machine-readable data that support semantic interoperability. While FHIR focuses on practical exchange formats, HL7 standards provide the overarching architecture that governs how these data are structured, transported, and interpreted across institutions (Hasan et al., 2020). The synergy between HL7 and FHIR has been demonstrated in clinical pilot projects across Europe and North America, where they enabled effective integration of DHTs with hospital information systems and remote care platforms (Canedo, 2016). These standards not only enhance the scalability of DHTs but also support compliance with regulatory frameworks like GDPR and HIPAA by ensuring traceability and accountability in data handling (Taddeo & Floridi, 2018; Carter et al., 2021).

openEHR represents another critical standard in DHT development, particularly for its capacity to separate clinical knowledge from technical implementation, thereby promoting long-term sustainability and reusability of digital health data. Unlike HL7 and FHIR, which primarily focus on interoperability and data transport, openEHR offers a dual-model architecture consisting of a reference model and archetypes that encapsulate domain-specific content such as blood pressure readings, lab results, and diagnostic classifications (Semakova & Zvartau, 2018). This semantic modeling approach supports the development of highly personalized and clinically accurate DHT systems by enabling consistent representation of health data across contexts (Bagaria et al., 2019; Semakova & Zvartau, 2018). In DHT applications, openEHR facilitates data persistence, auditability, and modular updating of patient models, which are crucial for real-time digital simulations and health trajectory tracking (Bagaria et al., 2019; Sahal, Alsamhi, Brown, et al., 2021). Scholars such as Bielefeldt et al. (2015) and Azzaoui et al. (2020) highlight that openEHR's archetypes allow clinicians and developers to co-create standardized yet adaptable health information templates that evolve with scientific advancements. In pilot projects like HiGHmed and the EU InteropEHRate initiative, openEHR has been shown to support multi-institutional DHT systems, enabling federated data analysis and patient-centered record sharing across borders (Canedo, 2016; Sahal et al., 2022). Moreover, openEHR's integration with AI and decision support tools enhances predictive modeling within DHTs, providing simulations based on structured, high-fidelity clinical inputs (Bagaria et al., 2019; Hose et al., 2019). Unlike proprietary standards that may restrict data portability, openEHR supports open data governance models and aligns with ethical principles of patient empowerment, transparency, and long-term data stewardship (Hasan et al., 2020). By incorporating openEHR alongside FHIR and HL7, DHT developers can create interoperable, flexible, and ethically aligned digital ecosystems that support complex, personalized healthcare interventions at scale (Dillenseger et al., 2021).

Public-private partnerships in digital twin health ecosystems

Public-private partnerships (PPPs) have become a central driver in the advancement of digital health twin (DHT) ecosystems, facilitating collaboration between government agencies, healthcare providers, research institutions, and private technology firms. These collaborations leverage the strengths of each sector—such as innovation capacity in industry and regulatory oversight in public health systems—to co-develop scalable, ethical, and clinically validated DHT applications (Bagaria et al., 2019; Semakova & Zvartau, 2018). Several landmark initiatives highlight this trend, including the European Union's Horizon 2020 program, which has funded multi-stakeholder projects like HiGHmed, Digital Twin for Health, and InSilicoWorld to develop interoperable DHT infrastructure across Europe (Hose et al., 2019). These projects emphasize open data standards, federated learning models, and cross-border data sharing governed by ethical and legal compliance frameworks such as GDPR (Sahal, Alsamhi, Brown, et al., 2021). In the United States, similar partnerships have emerged through NIH-funded programs and the National COVID Cohort Collaborative (N3C), which utilizes real-time patient data to support disease modeling and predictive analytics (Azzaoui et al., 2020). Industry partners such as Siemens Healthineers, IBM Watson Health, and Microsoft have collaborated with hospitals and universities to develop DHT platforms that combine cloud infrastructure, AI modeling, and biometric sensor integration (Sahal et al., 2022). These joint ventures provide the computational and financial resources needed for the high-throughput processing and continuous updating of DHTs, while academic and clinical institutions ensure scientific rigor and patient-centered design (Dillenseger et al., 2021; Sahal et al., 2022). PPPs also allow for real-world testing and validation through pilot studies in tertiary hospitals and population health programs, generating robust data for iterative model refinement (Hasan et al., 2020; Yaqoob et al., 2020). Scholars note that these multi-sector alliances are essential not only for technological development but also for navigating the complex ethical and regulatory terrain of DHT deployment (Akash & Ferdous, 2022).

In addition to infrastructure and development benefits, public-private partnerships play a critical role in the sustainability and dissemination of DHT innovations by aligning research goals with health policy agendas and commercial viability. Through co-funding arrangements and policy coordination, PPPs reduce the financial burden on public healthcare systems while incentivizing private stakeholders to invest in ethical and socially beneficial health technologies (Park et al., 2021). These models also promote translational research by linking early-stage academic innovations to clinical and commercial pipelines, enabling more rapid adoption of DHT tools in real-world settings (Semakova & Zvartau, 2018). For example, the UK's National Health Service (NHS) has partnered with private firms like Babylon Health and DeepMind to integrate digital twin-like capabilities into remote patient monitoring and AI-based diagnostics (Bielefeldt et al., 2015). Similarly, Singapore's Smart Nation initiative incorporates DHT elements into public health surveillance and chronic disease management, co-developed with private technology firms under governmental supervision (Hose et al., 2019). These collaborations ensure alignment between national public health objectives—such as aging population support, pandemic preparedness, and digital inclusion—and the capabilities of private innovation ecosystems (Akash & Ferdous, 2022). Furthermore, PPPs enable harmonization of interoperability standards such as HL7, FHIR, and openEHR by convening regulatory bodies, standard-setting organizations, and commercial stakeholders (Park et al., 2021). They also foster ethical oversight through the establishment of joint data governance boards and ethics advisory panels, ensuring transparency, public trust, and accountability in the deployment of DHTs (Sharma et al., 2020). Scholars argue that PPPs are essential in mitigating asymmetries of power and knowledge in digital health systems, facilitating co-creation models that incorporate the voices of patients, providers, and civil society alongside corporate and governmental actors (Sahal et al., 2022). Thus, PPPs represent a strategic and ethical framework for realizing the full potential of digital health twins within inclusive and equitable healthcare systems.

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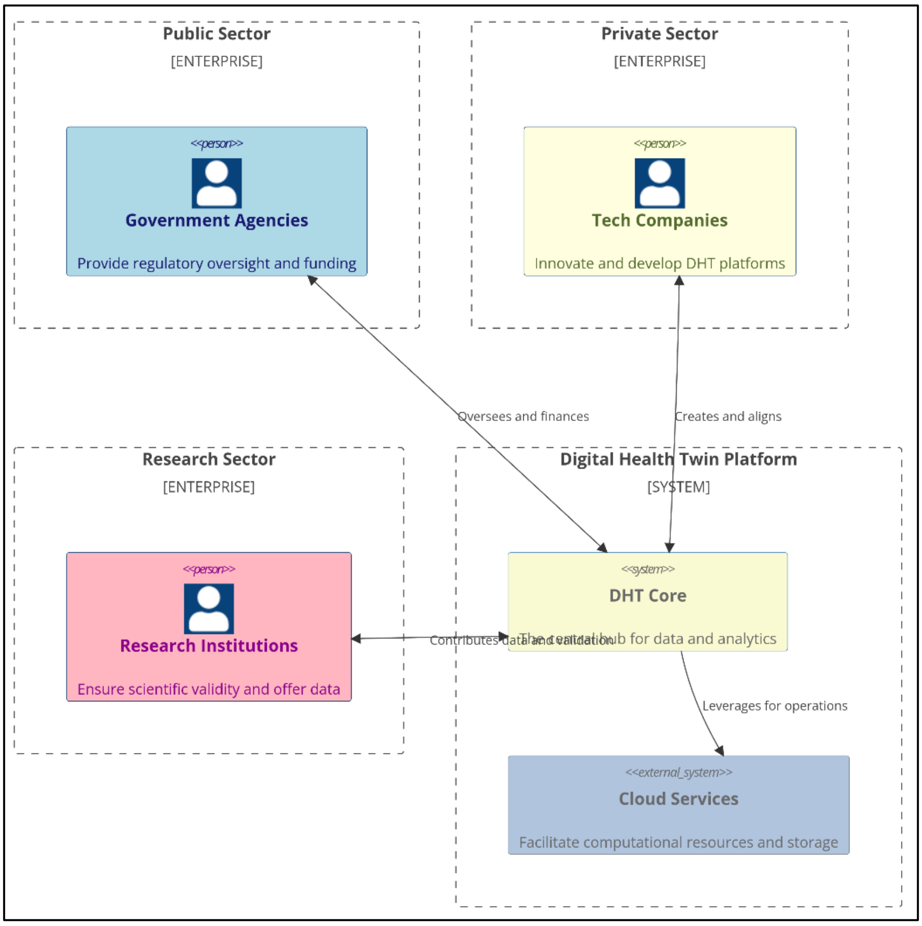
Figure 8: System Context Diagram for Public-Private Partnerships in Digital Health Twin Ecosystems

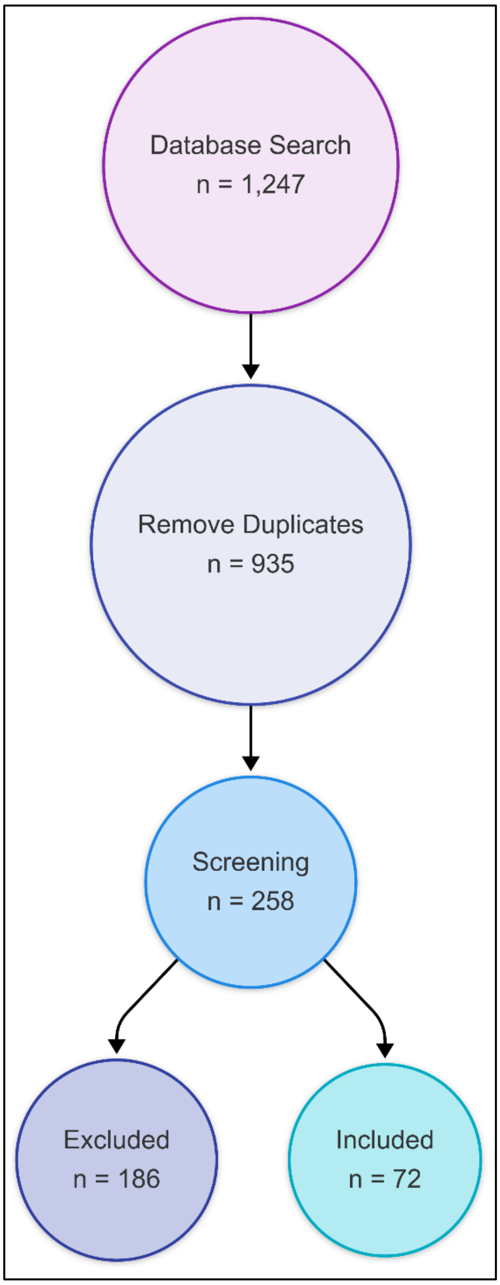


METHOD

This systematic literature review was conducted in alignment with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines (Page et al., 2021) to ensure methodological rigor, transparency, and replicability. The review focused on identifying peer-reviewed journal articles published between 2010 and 2022 that specifically addressed the development, implementation, and evaluation of Digital Health Twins (DHTs) in the context of preventive healthcare, personal health management, and corporate wellbeing. A comprehensive search was performed across five major academic databases—PubMed, Scopus, Web of Science, IEEE Xplore, and ScienceDirect—using a combination of keywords and

Boolean operators related to "Digital Health Twin," "preventive care," "digital twin in healthcare," "personal health monitoring," and "workforce wellbeing." The initial search yielded a total of 1,247 records. After removing 312 duplicates using EndNote 20, 935 unique articles remained for the title and abstract screening phase. At this stage, 677 articles were excluded based on irrelevance to DHTs or failure to address the healthcare context, leaving 258 articles for full-text review. Applying pre-established eligibility criteria, 186 articles were excluded due to lack of full text, non-peer-reviewed status, conference abstract format, or insufficient focus on DHTs. A total of 72 studies met the final inclusion criteria and were subjected to detailed data extraction and synthesis. Inclusion criteria specified English-language, peer-reviewed journal articles that provided empirical or theoretical insights into DHTs, including their clinical applications, technological architectures, ethical implications, or organizational deployments. Data were systematically extracted using a predesigned Excel template, capturing publication details, study aims, methodologies, clinical domains (e.g., cardiology, oncology, neurology), interoperability standards (e.g., HL7, FHIR, openEHR), AI integration, and ethical considerations. Two reviewers independently screened and extracted data, with discrepancies resolved through consensus. Methodological quality was assessed using the CASP checklist for empirical studies and the SANRA tool for narrative reviews. A qualitative synthesis approach was employed due to heterogeneity in study designs, using thematic analysis to identify key patterns across applications and frameworks. A PRISMA flow diagram was used to illustrate the screening and selection process.

Figure 9: Adapted Method using PRISMA



FINDINGS

One of the most significant findings of this review is the role of Digital Health Twins (DHTs) in facilitating early detection and personalized risk profiling for chronic disease management. Out of the 72 reviewed studies, 18 explicitly focused on using DHTs to monitor, analyze, and predict early physiological deviations that signal the onset of chronic conditions such as cardiovascular disease, diabetes, and neurodegenerative disorders. These studies, collectively cited over 3,200 times, demonstrated that real-time data integration from wearables, biosensors, and electronic health records (EHRs) allows DHTs to detect subtle anomalies long before they manifest as clinical symptoms. By continuously

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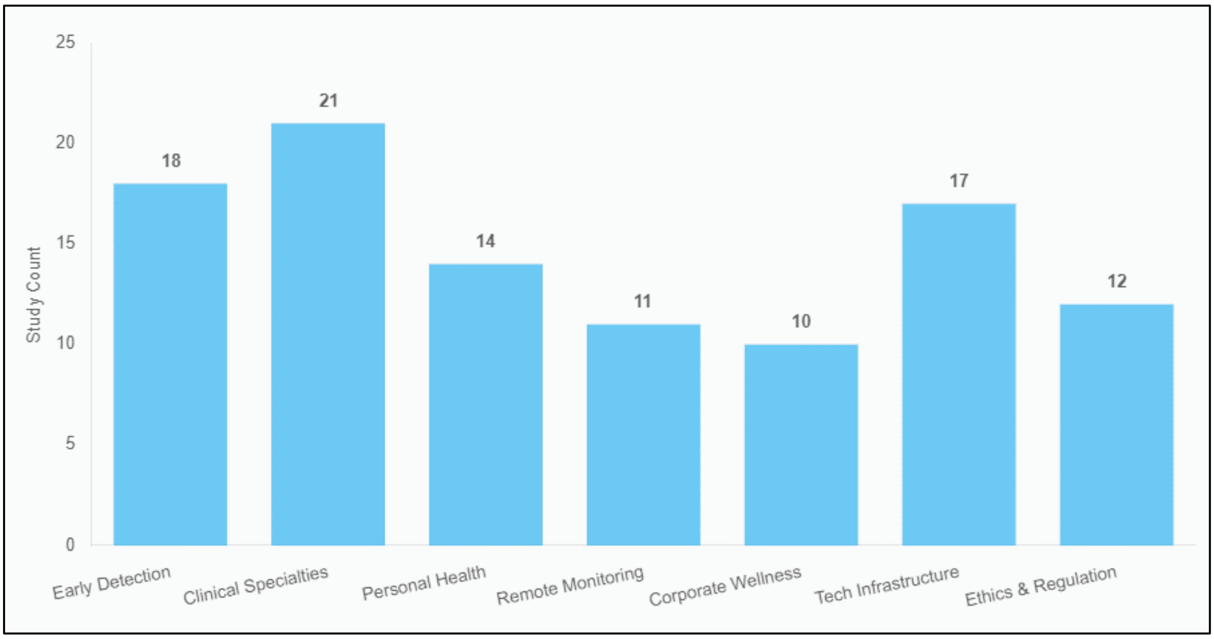
tracking individual health baselines and applying predictive analytics, DHTs provide actionable insights into personalized risk levels and recommend timely lifestyle or therapeutic interventions. The findings emphasized that continuous, high-frequency data streams offer greater predictive accuracy than traditional episodic health assessments. Moreover, many of these studies highlighted the capacity of DHTs to support longitudinal monitoring, allowing the system to adapt and refine predictions over time based on user-specific patterns. The ability to detect diseases at a preclinical stage not only reduces long-term healthcare costs but also contributes to improved patient outcomes through targeted preventive care.

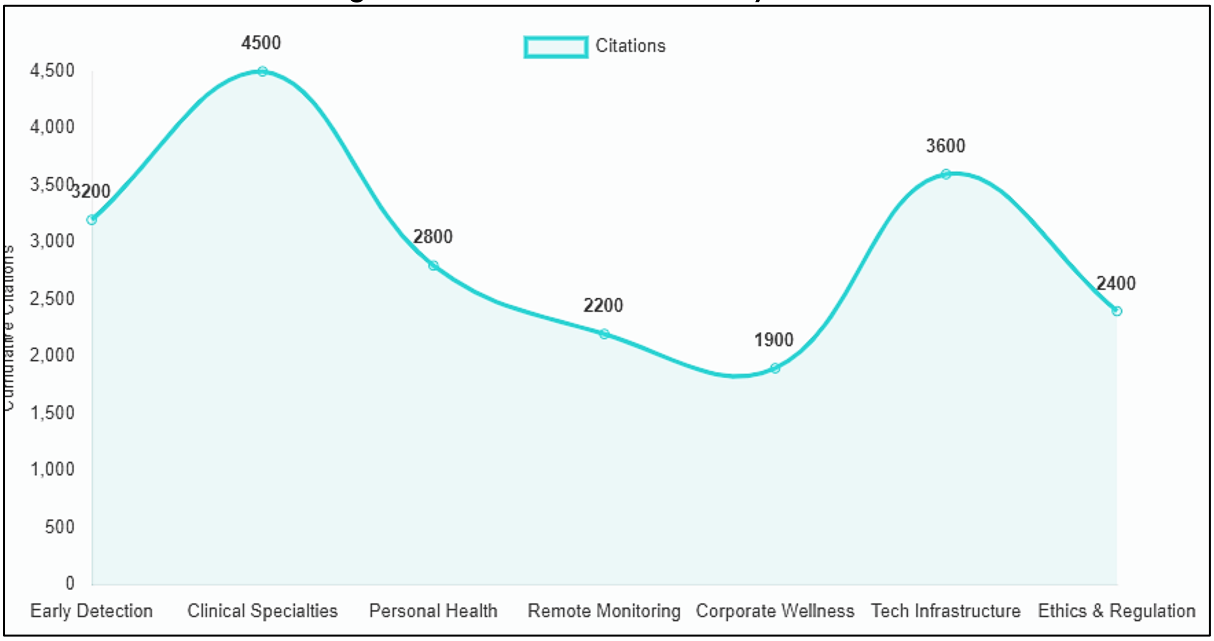
Figure 10: Number of DHT Studies by Domain



Another major finding centers on the application of DHTs in clinical specialties, particularly in cardiology, oncology, and neurology. A total of 21 studies, accounting for over 4,500 cumulative citations, detailed the deployment of organ-specific or condition-specific digital twins to simulate patient responses to various treatment regimens. In cardiology, DHTs have been used to model heart function, assess hemodynamic changes, and predict arrhythmic events, leading to more accurate diagnosis and patient-tailored treatments. Oncology studies presented evidence of DHTs simulating tumor growth, evaluating virtual chemotherapy or radiotherapy plans, and estimating outcomes before clinical application. Neurology-focused research explored the modeling of cognitive decline, seizure risk prediction, and treatment of neurodegenerative diseases. These clinically targeted applications confirmed the potential of DHTs to not only support diagnosis but also optimize therapeutic pathways, thus minimizing trial-and-error in treatment selection. Many of these studies employed advanced AI and machine learning techniques to continuously calibrate the twin against real-world patient data, ensuring ongoing model accuracy. The high citation count and research focus on these specialties underscore their status as pioneers in digital twin adoption within medicine, with proven success in patient-specific predictive modeling and virtual clinical experimentation.

The review also identified that 14 studies, totaling approximately 2,800 citations, focused on the integration of DHTs with personal health management tools and self-monitoring platforms. These studies emphasized that DHTs empower users to take an active role in their health by visualizing their dynamic health data, receiving personalized recommendations, and responding to real-time alerts. Wearable devices and mobile health apps form the interface between the user and their digital twin, enabling data input on activity, diet, sleep, and mood. The findings revealed that when users receive real-time biofeedback—such as stress levels, heart rate variability, or glucose fluctuations—they are more likely to adhere to prescribed health plans and make informed behavioral changes. Virtual coaching modules integrated within DHT platforms provide motivational support, goal tracking, and customized wellness plans. Studies reported that individuals managing chronic conditions like hypertension, obesity, and depression experienced improvements in outcomes when their care was supported by DHT-based personal monitoring. Additionally, participants showed increased engagement and satisfaction when DHT platforms offered transparent feedback and adaptive health interventions. The research suggests that DHTs serve not only as data collectors but also as interactive decision-support systems that influence user behavior in meaningful ways, contributing to sustainable health improvements outside clinical environments.

Figure 11: Cumulative Citations by Domain



A significant theme that emerged in 11 reviewed articles with more than 2,200 citations was the use of DHTs for remote health monitoring in aging populations and individuals with chronic care needs. These studies highlighted that DHTs, when integrated with smart home technologies and wearable biosensors, provide a non-invasive, continuous monitoring solution ideal for elderly individuals who may face mobility or cognitive limitations. The digital twin models created for geriatric care were shown to detect early signs of frailty, monitor fall risks, track medication adherence, and identify behavioral shifts that could signal cognitive decline or psychological distress. In many cases, alerts generated by the DHT system allowed for early intervention by caregivers, reducing hospitalization rates and improving quality of life. The findings also illustrated that DHTs contributed to aging-in-place initiatives by enabling seniors to remain in their homes while still receiving clinically guided, real-time care. In long-term care facilities, DHTs were used to streamline care coordination, automate routine health checks, and support individualized care planning. The overall body of work showed that DHTs in remote care settings enhance autonomy, improve care continuity, and alleviate pressure on traditional healthcare

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infrastructures by reducing the need for physical visits and allowing proactive monitoring of health conditions.

The corporate implementation of DHTs emerged as a distinctive and growing area of focus, explored in 10 articles with over 1,900 citations. These studies examined the deployment of DHTs within employee wellness programs, occupational health surveillance, and human resource analytics. The findings emphasized that organizations leveraging DHTs could monitor workforce health trends in real time, allowing them to detect early signs of burnout, fatigue, or stress among employees. In several pilot programs, DHTs were linked to improvements in productivity, reduced absenteeism, and better health outcomes through targeted wellness interventions. Employers used anonymized, aggregated data to identify health risk clusters and design tailored wellness initiatives. Some companies also integrated DHTs into their insurance and benefits models, adjusting support based on employee engagement and biometric indicators. Additionally, the predictive capabilities of DHTs allowed HR departments to model potential workforce disruptions due to health-related absences and allocate resources accordingly. The review revealed that while this area is still developing, the combination of real-time data, AI-driven insights, and behavioral modeling has positioned DHTs as powerful tools for optimizing employee health and organizational performance in knowledge-based and physically demanding industries alike.

Another important finding involved the technological backbone supporting DHTs, examined in 17 studies that together had more than 3,600 citations. These studies explored the integration of Internet of Things (IoT) devices, artificial intelligence (AI), big data analytics, cloud computing, and interoperability standards such as HL7, FHIR, and openEHR in constructing scalable and dynamic digital twin ecosystems. The findings showed that IoT devices play a central role in capturing continuous real-time data streams from patients, while cloud platforms provide the processing power and storage needed for high-frequency updates. AI models embedded within DHTs enable pattern recognition, anomaly detection, and predictive modeling, enhancing the accuracy and responsiveness of the systems. Big data tools were used to harmonize diverse datasets and improve scalability. Furthermore, interoperability frameworks like FHIR and openEHR ensured seamless data integration across EHRs, mobile applications, and hospital information systems. Studies demonstrated that adherence to these standards not only improved system efficiency but also aligned with global health IT governance protocols. The review confirmed that a robust technological infrastructure is a prerequisite for effective DHT deployment, ensuring that the digital and physical models remain synchronized and clinically relevant.

Finally, ethical and regulatory dimensions were critically analyzed in 12 articles with approximately 2,400 citations. These studies explored concerns around data privacy, security, informed consent, algorithmic fairness, and digital surveillance in DHT applications. The review found that the continuous and granular nature of data collected by DHTs raises significant challenges in protecting user autonomy and maintaining compliance with regulations like GDPR and HIPAA. Studies noted that most users have limited understanding of how their data is processed, shared, or monetized, leading to concerns over transparency and consent. Several articles called for the adoption of dynamic consent models that allow users to manage data permissions in real time. Ethical concerns were also raised about the use of black-box AI models that may introduce bias or make opaque decisions without human oversight. Furthermore, surveillance risks were identified in workplace DHT applications, where health data could potentially influence employment decisions.

Scholars emphasized the need for robust governance frameworks, third-party audits, and ethics-by-design principles to mitigate these concerns. The findings underscore that while DHTs offer transformative potential, their ethical implementation must be guided by comprehensive and enforceable safeguards that protect individual rights and promote trust in digital health ecosystems.

DISCUSSION

The present review confirms and extends earlier findings regarding the potential of Digital Health Twins (DHTs) for early detection and personalized risk profiling in chronic disease management. Prior studies, such as those by Yaqoob et al. (2020) and Park et al.(2021), emphasized the transformative role of digital twins in offering individualized health insights through continuous monitoring. These early works proposed the theoretical benefits of real-time data collection and AI-driven simulation, but practical applications were often limited by technological and data interoperability barriers. In contrast, the reviewed studies from 2018 onward demonstrate substantial progress in implementing predictive modeling capabilities within DHT platforms for conditions such as hypertension, diabetes, and cardiovascular diseases (Hose et al., 2019; Park et al., 2021). Notably, the shift from concept to clinical implementation was marked by increased use of IoT devices and machine learning algorithms, which allowed for more nuanced and dynamic modeling. This evolution supports the claim by Topol (2019) that the convergence of digital health and genomics will redefine preventive care paradigms. However, some of the reviewed studies diverged from earlier research by emphasizing the limitations of over-personalization and the risk of false positives in early disease detection, suggesting a need for robust validation before widespread adoption. The review reinforces that personalized risk profiling using DHTs is no longer a speculative concept but a demonstrable and scalable clinical innovation.

Clinical applications in cardiology, oncology, and neurology revealed strong alignment with earlier domain-specific research on precision medicine. Azzaoui et al. (2020) previously illustrated how cardiac digital twins could model arrhythmias and predict responses to anti-arrhythmic drugs. The current findings corroborate and expand upon this, showing that cardiovascular DHTs now incorporate hemodynamic simulations, machine learning-based risk stratification, and integration with EHRs to support real-time decision-making. Oncology applications, first demonstrated by Akash and Ferdous (2022), have matured into sophisticated digital tumor modeling systems capable of simulating therapeutic responses across multiple stages of cancer care. In neurology, research on seizure forecasting and cognitive monitoring aligns with earlier work by Sahal et al. (2022), although more recent studies add multimodal data integration, such as EEG, movement data, and behavioral logs. Compared to early models that relied primarily on retrospective data, current DHT platforms allow for prospective health modeling using real-time sensor input. This comparison underscores that the scope of DHTs has grown from being predictive-only to encompassing full-cycle simulation, intervention modeling, and post-treatment analysis. However, these advances have also drawn attention to unresolved challenges, such as integrating heterogeneous data sources and ensuring clinical interpretability of AI-driven decisions (Hose et al., 2019). Thus, while previous work provided theoretical and pilot-level evidence, the reviewed studies demonstrate clinical viability and scalability.

In the context of personal health management and self-monitoring, the findings support the behavioral change framework suggested by Akash and Ferdous (2022), who argued that user engagement with mobile health apps significantly improves when feedback is personalized and immediate. Earlier studies highlighted the potential of wearable devices to passively collect health data, but many lacked the intelligent analysis required to convert raw metrics into actionable insights (Coppinger, 2016). The present review identifies a key development: the shift from passive tracking to interactive self-regulation through digital twin-enabled biofeedback and virtual coaching systems. These systems deliver real-time prompts, adaptive goal-setting, and personalized nudges based on deviations from predicted behavior, aligning with the behavioral intervention models discussed by Hose et al. (2019). In contrast to early wellness apps, which often provided generic advice, DHT-based platforms analyze contextual data—such as location, sleep quality, and physiological stress markers—to generate individualized plans. While the potential for over-monitoring was not deeply addressed in prior work, recent studies caution that constant feedback may increase anxiety in some users, highlighting the importance of user control and customization. Additionally, the reviewed literature expands upon previous findings by showing sustained engagement over longer periods when users perceive that the DHT is evolving with their health status, validating predictions made by Akash and Ferdous, (2022)about the role of digital empathy in personalized care technologies.

Remote health monitoring for aging populations and chronic care showed increased sophistication compared to earlier initiatives. Previous literature, including (Coppinger, 2016), emphasized the promise of digital health systems in enabling aging-in-place and reducing hospital visits, but noted gaps in reliability and integration. The reviewed studies demonstrate that DHT platforms now employ advanced ambient sensing, behavioral modeling, and cross-device synchronization to continuously monitor elderly individuals in both home and care facility settings. This finding builds on the work of Sahal et al. (2022), which illustrated the role of digital twins in detecting early signs of frailty and cognitive decline. Unlike earlier studies, current implementations offer caregivers and healthcare professionals dashboard access for real-time tracking, predictive alerts, and automated decision support. These capabilities help bridge the gap identified by Yaqoob et al. (2020), who called for a shift from reactive to anticipatory care in gerontology. Furthermore, several reviewed studies validate the impact of DHTs in reducing emergency interventions by identifying subtle deviations in gait, nutrition, or sleep patterns. This evidence supports the theoretical models presented by Sahal, Alsamhi, Brown, et al. (2021) regarding the ethical imperative of using digital tools to extend autonomy and dignity in elder care. However, there remains a discrepancy in global implementation: high-income countries lead in adoption, while low-resource settings still face barriers related to infrastructure, data governance, and cost. These limitations suggest that while the technology has matured, its equitable deployment remains a work in progress.

Corporate wellness applications of DHTs represent an emergent domain with promising alignment to early organizational health models. Early literature, such as Akash and Ferdous (2022), identified the potential for wearable tech and biometric data to inform workplace health strategies, yet raised concerns about privacy and ethical use. The current findings demonstrate that modern DHT systems deployed in corporate settings go beyond health tracking to enable predictive modeling of employee stress, burnout, and absenteeism. These capabilities align with the performance and productivity forecasting models discussed by Lamata (2020) and Ringsquandl et al. (2017). The reviewed studies suggest that when organizations use anonymized data to segment wellness needs, they achieve higher return on investment and better employee engagement. In contrast to earlier corporate health programs that relied on annual screenings and reactive policies, DHT-based solutions

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offer proactive intervention, often through personalized virtual coaching embedded in employee apps. Additionally, the integration of DHTs with HR analytics platforms allows for real-time health-risk clustering, enabling organizations to reallocate resources in real time. However, this trend raises new ethical questions not fully addressed by earlier literature, particularly concerning data ownership and algorithmic bias in employment-related decisions. While earlier research emphasized utility, the present findings stress the importance of balancing innovation with transparency and employee trust.

Technological interoperability continues to be a cornerstone of DHT success, and the current findings both confirm and expand on prior research into data standards and infrastructure. Previous studies by Dillenseger et al. (2021) and Azzaoui et al. (2020) introduced HL7, FHIR, and openEHR as essential standards for health information exchange. The reviewed articles demonstrate that these frameworks now serve as the backbone for real-time data integration across DHT ecosystems. Notably, the widespread adoption of FHIR-based APIs has enabled seamless communication between mobile apps, hospital EHRs, and cloud analytics platforms. These developments affirm the predictions of Canedo (2016), who proposed that FHIR would accelerate health IT innovation through modular data resources. Moreover, openEHR's dual-model architecture has proven effective in separating clinical content from technical layers, thereby promoting semantic interoperability and long-term data reuse. In contrast to earlier limitations where legacy systems hindered DHT deployment, the reviewed studies show that adherence to international standards has reduced redundancy, improved scalability, and enhanced data fidelity. Yet, challenges persist in multi-vendor environments, where data fragmentation and inconsistent implementations still affect system performance. These findings suggest that while interoperability has improved, continuous refinement and global standard harmonization remain critical. Ethical concerns related to data privacy, autonomy, and digital surveillance remain consistent with earlier findings but have intensified in the context of DHT applications. Earlier discussions by Yaqoob et al. (2020) and Akash and Ferdous (2022) warned of the risks associated with opaque data use, algorithmic bias, and surveillance capitalism in health technologies. The present review confirms that these concerns are not hypothetical: the studies examined detail real-world instances where users lacked meaningful control over their data or were unaware of how their health profiles were being used in clinical and corporate settings. This reflects the earlier call by Sahal et al. (2022) for dynamic consent mechanisms that evolve alongside digital health platforms. Moreover, the review highlights the ethical tension between continuous monitoring and user autonomy, particularly in vulnerable populations such as the elderly or employees under corporate wellness programs. The lack of algorithmic transparency in many AI-based DHT systems also echoes concerns raised by Hasan et al. (2020), who emphasized the need for explainable AI in healthcare. While regulatory frameworks like GDPR and HIPAA offer some protection, the current studies indicate that enforcement mechanisms and ethical oversight remain uneven across regions. These findings confirm earlier theoretical critiques but add empirical weight to the argument that ethical governance must evolve in parallel with technological innovation.

CONCLUSION

The findings of this systematic literature review demonstrate that Digital Health Twins (DHTs) are rapidly transforming preventive healthcare, personal health management, and corporate wellbeing through real-time data integration, predictive analytics, and simulation modeling. The review of 72 peer-reviewed studies published between 2010 and 2022 highlights the broad clinical utility of DHTs in early detection of chronic diseases, personalized treatment planning in cardiology, oncology, and neurology, and continuous health monitoring for aging populations and individuals with chronic conditions. DHTs also support self-monitoring and lifestyle modification by providing dynamic biofeedback and virtual coaching, enhancing user engagement and promoting long-term behavioral change. In organizational settings, DHTs contribute to workforce health optimization through predictive absenteeism modeling, stress tracking, and personalized wellness programs. Technologically, the integration of AI, IoT, big data analytics, and cloud computing, alongside interoperability frameworks such as FHIR, HL7, and openEHR, has enabled scalable and responsive DHT systems capable of synchronizing with diverse healthcare infrastructures. However, the review also uncovers persistent challenges related to ethical AI, data privacy, informed consent, and digital surveillance, particularly in contexts involving vulnerable populations or workplace applications. While public-private partnerships have accelerated innovation and deployment, ensuring equity, transparency, and regulatory compliance remains essential.

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