

AI Digital Twins for Healthcare and Inner Engineering: A Perspective

Prof. Dr. Son Vuong
University of British Columbia
Vancouver, Canada

Abstract

*The ultimate goal of human beings is to elevate wisdom and sustain good health and happiness, that can be achieved via **inner engineering (IE)** and AI Digital Twins, collectively forming the so-called **Internet of Minds (IOM)** and **Revolution 5.0**.*

In this paper, we shall present some ground breaking research in leveraging the AI Digital Twin and inner engineering technologies to transform wisdom and healthcare. The paper will elucidate the fundamental principles of digital twins, their construction, and their wide-ranging applications. We shall highlight through a case study of diabetes management how digital twins and AI enable personalized development and treatment, predict disease progression, and optimize interventions, ultimately improving personalized outcomes in inner engineering toward enlightenment.

1. Introduction

The ultimate goals of human beings vary greatly across cultures, philosophies, and individuals. However, it boils down to two important elements: **health and wisdom, including personal growth, happiness and enlightenment**, that are the most common and timeless aspirations that humans strive for, and that can be achieved via digital twins and inner engineering.

The healthcare industry as well as inner engineering are on the verge of a revolution, driven by the convergence of technological advancements, AI, data analytics, and personalized medicine. One of the most promising innovations in this space is the **Digital Twin**, a virtual replica of a physical system, process, or, in this case, a human being. By creating a digital duplicate of a patient's physiology, anatomy, and medical history, healthcare providers can simulate, predict, and optimize treatment outcomes, via AI methods, leading to more effective, personalized, and cost-efficient care.

The potential benefits of AI Digital Twins in healthcare and inner engineering are vast, ranging from improved disease diagnosis and treatment to enhanced patient engagement, outcomes, personal growth and fulfillment. Moreover, Digital Twins can facilitate the development of more effective prevention strategies, reduce medical errors, and optimize resource allocation. As the healthcare industry continues to grapple with the challenges of an aging population, rising healthcare costs, and

increasingly complex medical conditions, the adoption of Digital Twins is poised to play a transformative role in shaping the future of healthcare and wisdom development.

Inner Engineering is a comprehensive framework for personal growth, self-awareness, and spiritual evolution. The key components comprise: self-awareness, consciousness, energy, and spirituality. By applying the principles and practices of inner engineering, individuals can transform their lives, achieving a state of inner peace and happiness, thereby reaching their full potential. The Digital Twin is deemed to offer an effective approach to inner engineering.

This paper aims to explore the concept of Digital Twins in healthcare and inner engineering, discussing its potential applications, benefits, and challenges. We will delve into the current state of Digital Twin technology via a case study of diabetes management, its relevance to various healthcare and personal growth domains, and offer a glimpse into future research of Digital Twin in inner engineering.

2. Background and Related Work

2.1 Background

The concept of digital twins was first introduced in 2002 by **Dr. Michael Grieves**, a researcher at the University of Michigan. Initially, digital twins were used in the aerospace and defense industries to simulate the behavior of complex systems. Over time, the concept of digital twins has expanded to other industries, including manufacturing, healthcare, and energy. We foresee that it can be well applicable to inner engineering for personal growth, wisdom development and spiritual enlightenment.

A digital twin is a virtual replica of a physical object, system, or process. It is a digital representation of the real-world entity, which can be used to simulate, predict, and optimize its behavior. The concept of digital twins has been around for several decades, but it has gained significant attention in recent years due to advances in technologies such as artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT). Since AI and ML are nowadays become integral parts of digital twins, we shall refer to such digital twins as as **AI digital twins**, or simply **Digital Twins** or **AI Twins** or **AI Clones**.

Just like AI Agent, Digital Twin belongs to the **Foundational Model Layer** in the AI stack shown in Figure 1. Most of the opportunities lie however in the AI unlimited applications, illustrated in **Applications Layer**. Both AI Agent and Digital Twin technologies have received paramount investment in 2024 and are expected to surge further in 2025 and beyond.

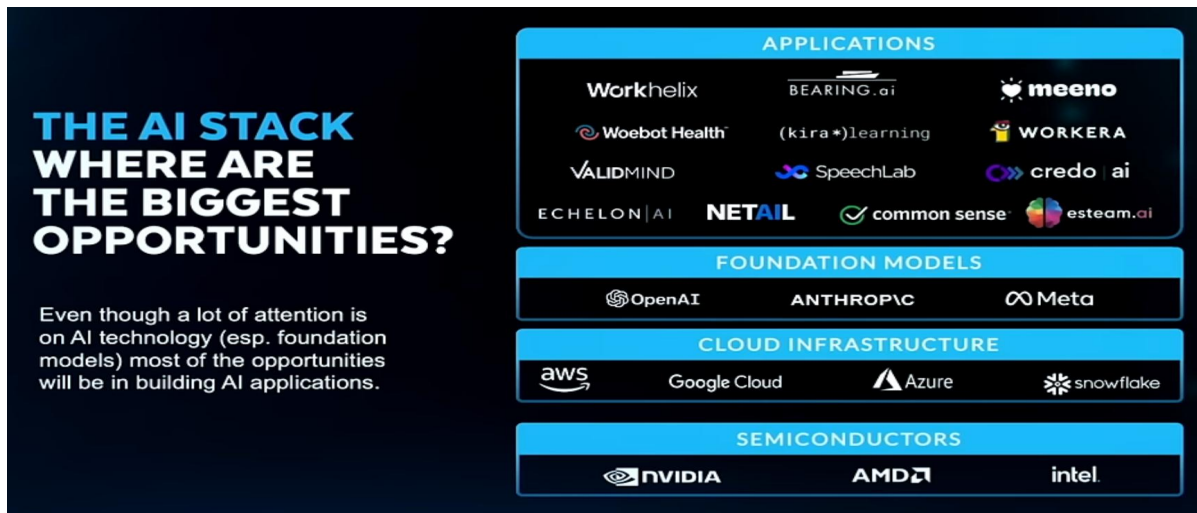


Figure 1. AI stack (image credit: Andrew Ng’s keynote talk at Snowflake BUILD 2024 <https://www.snowflake.com/build>)

Digital twins have several key characteristics that distinguish them from other digital representations. These include:

- **Real-time Data Integration:** Digital twins integrate real-time data from sensors, IoT devices, and other sources to create an accurate and up-to-date representation of the physical entity.
- **Simulation and Prediction:** Digital twins use advanced algorithms and simulation techniques to predict the behavior of the physical entity under different scenarios.
- **Virtual-Physical Interaction:** Digital twins enable virtual-physical interaction, allowing users to interact with the virtual representation of the physical entity.
- **Autonomy and Self-Optimization:** Digital twins can operate autonomously and self-optimize their behavior based on real-time data and simulation results.

It is interesting to note that a physical entity can have multiple associated digital twins. This concept is often referred to as "**multi-twinning**" or "**hierarchical twinning.**"

In this context, multiple digital twins can represent different aspects, scales, or levels of abstraction of the same physical entity. Here are some possible scenarios:

- **Component-level twins:** A complex physical system, like an aircraft engine, can have multiple digital twins representing individual components, such as the compressor, turbine, or fuel system.
- **System-level twins:** A physical entity, like a building, can have multiple digital twins representing different systems, such as HVAC, electrical, or plumbing.

- **Scale-dependent twins:** A physical entity, like a city, can have multiple digital twins representing different scales, such as a detailed model of a single building, a neighborhood, or the entire city.
- **Domain-specific twins:** A physical entity, like a patient, can have multiple digital twins representing different domains, such as a medical twin for health monitoring, a biomechanical twin for movement analysis, or a nutritional twin for dietary planning.

Having multiple digital twins associated with a physical entity can provide a more comprehensive understanding of its behavior, performance, and interactions with its environment.

Naturally, multiple digital twins can communicate with each other [Das 2022]. This concept is often referred to as "**digital twin synchronization**" or "**digital twin communication.**"

Digital twin communication enables the exchange of data, information, and insights between multiple digital twins, allowing them to:

- **Synchronize their state:** Ensure consistency and accuracy across multiple digital twins.
- **Share knowledge and insights:** Enable digital twins to learn from each other and improve their decision-making capabilities.
- **Coordinate actions:** Facilitate collaboration and coordination between digital twins to achieve common goals.
- **Improve overall system performance:** Enhance the efficiency, reliability, and resilience of the physical system being represented by the digital twins.

Digital twin communication can be achieved through various means, including:

- **APIs (Application Programming Interfaces):** Enable digital twins to communicate with each other through standardized APIs.
- **Message Queues:** Allow digital twins to exchange messages and data through message queues.
- **Data Lakes:** Provide a centralized repository for digital twins to share and access data.
- **Cloud-based Platforms:** Offer a scalable and secure environment for digital twins to communicate and interact.

Examples of digital twin communication include:

- **Smart Cities:** Digital twins of buildings, transportation systems, and energy grids can communicate to optimize energy efficiency, traffic flow, and public services.

- **Industrial Automation:** Digital twins of machines, production lines, and supply chains can communicate to optimize production, reduce downtime, and improve product quality.
- **Healthcare** [Kam 2021]: Digital twins of patients, medical devices, and healthcare systems can communicate to improve patient outcomes, optimize treatment plans, and streamline clinical workflows.

Investment in digital twins has been increasing drastically in the past few years and is expected to surge in 2025, driven by increasing adoption across various industries.

2.2. Key Investment Areas:

Here are some practical digital twin systems in use:

- **Industrial and Manufacturing**

1. *GE's Digital Twin for Power Plants:* GE's digital twin platform monitors and optimizes power plant performance in real-time.
2. *Siemens' Digital Twin for Industrial Automation:* Siemens' digital twin platform simulates and optimizes industrial automation systems.
3. *Dassault Systèmes' Digital Twin for Aerospace:* Dassault Systèmes' digital twin platform simulates and optimizes aerospace systems.

- **Infrastructure and Construction**

1. *Singapore's Digital Twin for Urban Planning:* Singapore's digital twin platform simulates and optimizes urban planning and development.
2. *New York City's Digital Twin for Infrastructure Management:* New York City's digital twin platform monitors and optimizes infrastructure performance.
3. *Bentley Systems' Digital Twin for Construction:* Bentley Systems' digital twin platform simulates and optimizes construction projects.

- **Healthcare**

1. *IBM's Digital Twin for Patient Care:* IBM's digital twin platform simulates and optimizes patient care pathways.
2. *Philips' Digital Twin for Medical Imaging:* Philips' digital twin platform simulates and optimizes medical imaging procedures.
3. *Stanford Health Care's Digital Twin for Hospital Operations:* Stanford Health Care's digital twin platform monitors and optimizes hospital operations.

- **Transportation**

1. *NASA's Digital Twin for Space Exploration*: NASA's digital twin platform simulates and optimizes space exploration missions.
2. *Volkswagen's Digital Twin for Vehicle Development*: Volkswagen's digital twin platform simulates and optimizes vehicle development.
3. *Siemens' Digital Twin for Rail Network Optimization*: Siemens' digital twin platform simulates and optimizes rail network performance.

- **Energy and Utilities**

1. *National Grid's Digital Twin for Energy Network Optimization*: National Grid's digital twin platform simulates and optimizes energy network performance.
2. *Shell's Digital Twin for Oil and Gas Operations*: Shell's digital twin platform simulates and optimizes oil and gas operations.
3. *Duke Energy's Digital Twin for Smart Grid Management*: Duke Energy's digital twin platform monitors and optimizes smart grid performance.

2.3. Major Digital Twin Platforms and Tools:

Major companies that provide tools for building digital twins include the following:

- **Siemens**: Siemens provides a range of tools and platforms for building digital twins, including Siemens MindSphere, Siemens Simcenter, and Siemens NX.
- **Dassault Systèmes**: Dassault Systèmes provides a range of tools and platforms for building digital twins, including Dassault Systèmes 3DEXPERIENCE, Dassault Systèmes CATIA, and Dassault Systèmes SIMULIA.
- **PTC**: PTC provides a range of tools and platforms for building digital twins, including PTC ThingWorx, PTC Windchill, and PTC Creo.
- **General Electric (GE)**: GE provides a range of tools and platforms for building digital twins, including GE Predix, GE Digital Twin, and GE Asset Performance Management.
- **Microsoft**: Microsoft provides a range of tools and platforms for building digital twins, including Microsoft Azure Digital Twins, Microsoft Azure IoT Hub, and Microsoft Azure Machine Learning.
- **Ansys**: Ansys provides a range of tools and platforms for building digital twins, including Ansys Twin Builder, Ansys Autonomy, and Ansys Speos.
- **Altair**: Altair provides a range of tools and platforms for building digital twins, including Altair Inspire, Altair Activate, and Altair HyperWorks.
- **SAP**: SAP provides a range of tools and platforms for building digital twins, including SAP Leonardo, SAP IoT, and SAP Predictive Maintenance.
- **Oracle**: Oracle provides a range of tools and platforms for building digital twins, including Oracle IoT Cloud, Oracle Digital Twin, and Oracle Predictive Maintenance.

These companies provide a range of tools and platforms for building digital twins in the following categories:

- **Computer-Aided Design (CAD) software:** For designing and simulating digital twins.
- **Simulation software:** For simulating the behavior of digital twins.
- **Internet of Things (IoT) platforms:** For connecting digital twins to physical systems and devices.
- **Cloud computing platforms:** For hosting and managing digital twins.
- **Artificial intelligence (AI) and machine learning (ML) platforms:** For analyzing data from digital twins and making predictions.

3. Digital Twin for Diabetes Management as an Example [Ras 2024]

Diabetes management is a complex and dynamic process, requiring personalized and adaptive approaches to achieve optimal glucose control. Recent advances in Artificial Intelligence (AI) and Digital Twin technologies have paved the way for innovative solutions in diabetes management [Chu 2023]. This section explores the concept of Digital Twin for diabetes management, highlighting its potential benefits, technical requirements, and future directions. This case study is based on collaborative substantive research of Professor Juan Li's research group at NDSU [Ras 2024].

3.1 Concept and Architecture

Diabetes management research covers essentially several important areas, including:

- Risk prediction models seek to identify individuals at heightened risk based on genetic, lifestyle, and environmental factors, opening doors to proactive or preventative interventions [Apa 2021] [Ndj 2020].
- Personalized treatment planning aims to tailor medication, diet, and exercise regimens to an individual's unique biology and preferences, maximizing therapeutic outcomes and minimizing side effects [Sub 2014].
- Preventive strategies focus on identifying modifiable factors like diet, physical activity, and exposure to environmental toxins, aiming to reduce the likelihood of developing diabetes or to slow disease progression in those already diagnosed [Bac 2013].
- Integration of the above research areas in a holistic framework, allowing for effective personalized and dynamic risk assessments, treatment plans, and preventive measures.

This case study results in the following contributions:

- **Holistic Approach:** Via integrating various physiological, lifestyle, social, environmental, and dietary factors in a unified framework.
- **A patient-centric framework:** The proposed framework is built around personal health knowledge graphs (PHKGs) to capture the complex and evolving relationships among diverse data sources such as patient history, lifestyle, preferences, goals, and environmental factors and patients' self-acquired knowledge.
- **Data Integration and Interoperability:** The ontology HL7 standards [HL7 2023] is adopted in the framework to promote seamless interaction across devices, applications, programs, and institutional boundaries.
- **Extensibility and Adaptability:** PHKGs offer a flexible structure, allowing them to expand adaptively with dynamic new knowledge about the patient.
- **Demonstrated Use Cases:** We showcase the usage of the digital twin framework for real-world diabetes management applications, including predicting glucose levels, optimizing insulin dosage, offering lifestyle recommendations, tailored dietary advice, and health data visualization.

Fundamentally, a Digital Twin for diabetes management is a virtual replica of an individual's physiological system, integrating AI and Machine Learning (ML) algorithms to simulate glucose dynamics, predict treatment outcomes, and optimize personalized care. The architecture of an AI Digital Twin for diabetes management typically consists of the following components:

- **Data Integration Layer:** This layer aggregates and integrates data from various sources, including *electronic health records (EHRs)*, *continuous glucose monitoring systems (CGMS)*, insulin pumps, and wearable devices.
- **Physiological Modeling Layer:** This layer employs mathematical models to simulate glucose dynamics, insulin sensitivity, and other physiological processes relevant to diabetes management.
- **AI and ML Layer:** This layer utilizes AI and ML algorithms to analyze data, identify patterns, and make predictions about treatment outcomes and glucose control [Apa 2021].
- **Decision Support Layer:** This layer provides personalized recommendations for diabetes management, including insulin dosing, medication adjustments, and lifestyle modifications.

3.2 Construction of Digital Twins for Diabetes Management

This process involves the generation dynamic virtual representations of a patient's health state that enable the simulation of behavior and prediction of outcomes and allow for personalized insights. These virtual representations are designed to be adaptive, continuously updating with real-time data to reflect the patient's current health status accurately. **Figure 2** shows the framework of the proposed digital twins, so-called **GlycoTwin**. This framework integrates various data sources to construct a

comprehensive model of the individual’s health. The framework comprises multiple layers, starting with ontology development, data collection and integration, personal health knowledge graph creation, and applications.

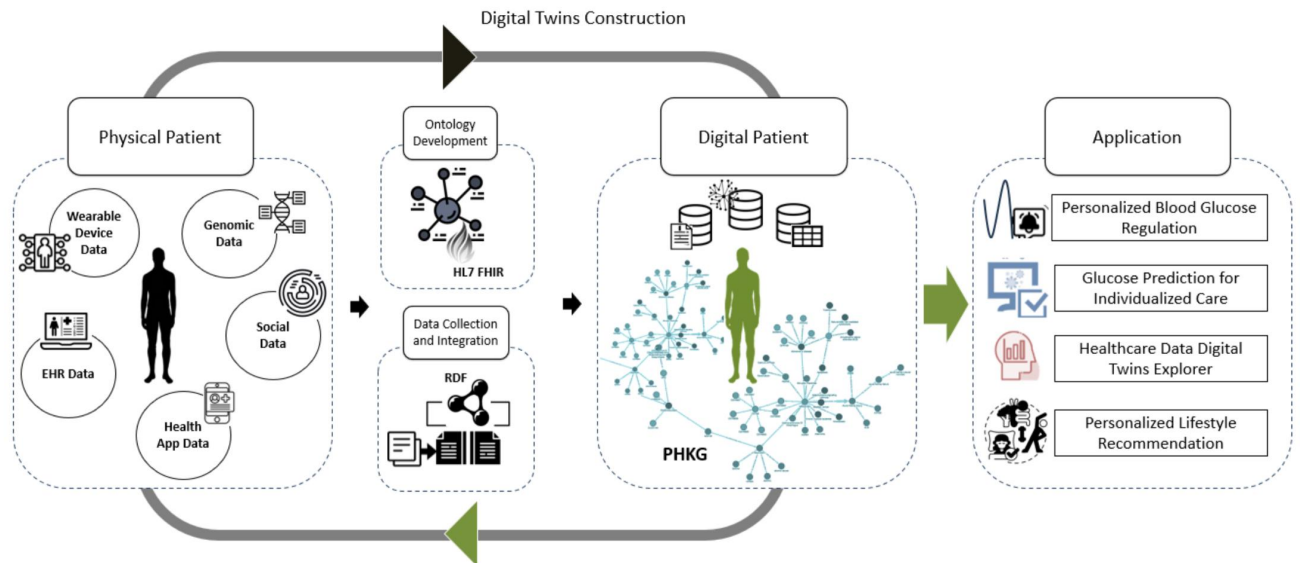


Figure 2. GlycoTwin: Digital Twin for personalized diabetes management.

Details of the framework for constructing Digital Twins are presented in the remainder of this section.

3.2.1. *Ontology Development*

At the cornerstone is the development of a robust and standardized ontology, aligned with HL7 FHIR standards [Kio 2019] to ensure interoperability and adherence to established industry practices. This health ontology is intricately designed to offer a comprehensive vocabulary and articulate the complex relationships inherent within the personal health domain, acting as the structural foundation upon which our digital twin models are constructed.

Our methodology for ontology development embraces a systematic, top-down approach, initiating with broad health-related categories such as “Medical Condition” and progressively dissecting these into more specific subcategories like “Diabetes”. This hierarchical structure allows for a nuanced categorization of health conditions. Each concept within the ontology is enriched with properties that detail its attributes and the relationships it shares with other concepts. These are divided into object properties, which connect different concepts within the ontology, and data properties, which link concepts to specific values, facilitating a detailed and relational representation of health data.

This robust framework is instrumental in elevating the level of personalization and efficacy within healthcare delivery. By laying down a solid foundation, we are able to tailor healthcare solutions to individual needs, thereby optimizing the overall healthcare experience. This commitment to enhancing personalization directly translates into more effective healthcare outcomes, ensuring that each patient receives care that is specifically designed to meet their unique health requirements.

3.2.2. Data Collection and Integration

Our approach to data collection and integration is expansive and meticulous. We tap into a wide array of healthcare data sources, including but not limited to electronic health records (EHRs), inputs from wearable devices, mobile health applications, and direct patient-generated data. Each of these sources plays a pivotal role in painting a comprehensive picture of a patient's health landscape, offering unique insights that are integral to the construction of a detailed and accurate digital twin.

A rigorous quality control process is initiated to ensure the integrity and usability of the collected data. This critical phase addresses common data quality issues, such as missing values, inconsistencies, and outliers, which are inherent challenges in dealing with diverse healthcare datasets. Following the rectification of these issues, the data undergo a transformation process. This crucial step involves mapping the raw data onto the predefined concepts and relationships within our health ontology. The aim here is to achieve a unified and standardized representation of the data, ensuring that it aligns seamlessly with the structured framework of our ontology, thereby facilitating an accurate and effective data integration.

The cornerstone of our data integration strategy is the innovative use of the GLAV (Global–Local as View) framework [30]. This advanced framework stands out from traditional data integration approaches, such as GAV (Global as View) and LAV (Local as View), by offering a more dynamic and flexible mapping capability. The essence of GLAV lies in its ability to support bidirectional mappings, which is particularly advantageous when dealing with the voluminous and intricate nature of healthcare datasets. This flexibility is crucial for accommodating the complex interrelations and the heterogeneity inherent in healthcare data, thereby ensuring a more cohesive and comprehensive integration process.

To further refine the data integration process and enhance the accuracy of mappings, we employ Conditional Random Fields (CRFs). These advanced probabilistic graphical models are renowned for their proficiency in pattern recognition and their ability to learn complex patterns within data. By leveraging CRFs, we are able to discern and accurately map the intricate features of source data—such as column names and data types—onto the relevant concepts within our ontology. This level of precision in mapping is pivotal for ensuring that the integrated data are not only accurate but also meaningful within the context of the digital twins, enabling a richer and more nuanced representation of the patient's health status. Through this comprehensive and nuanced approach to data collection and integration, we ensure

the assembling of a rich and coherent dataset. This dataset forms the backbone of our digital twins, providing the depth and breadth of information necessary for simulating realistic and detailed virtual representations of patients' health conditions, thereby paving the way for personalized and precise healthcare interventions.

3.2.3. Personal Health Knowledge Graph (PHKG) Construction

The construction of the personal health knowledge graph (PHKG) is a critical phase that follows the meticulous integration and transformation of health data. This pivotal transformation marks the transition of raw health data into a structured format that is amenable to semantic querying and reasoning, laying the groundwork for the robust instantiation of the knowledge graph. The PHKG is sculpted based on the intricacies of the predefined ontology, serving as a dynamic representation of a patient's health landscape.

The instantiation process within the PHKG begins with the systematic identification and creation of specific instances for each ontological concept derived from the integrated health data. For instance, an individual blood glucose measurement recorded in the health data is instantiated within the graph as a particular manifestation of the "Blood Glucose Level" concept. This step transforms abstract ontological concepts into concrete instances that reflect real-world data points related to the patient's health status. Simultaneously, the relationships among these instances, as delineated by the ontology through a network of object and data properties, are materialized as edges within the graph. These edges serve as the connective tissue between concept instances, weaving a complex web of relationships that mirrors the intricate, multifaceted nature of health data. For example, a "has Symptom" relationship might be instantiated to connect a "Diabetes" concept instance with a "Frequent Urination" symptom instance, thereby encapsulating the symptomatology associated with the condition within the patient's health profile.

The PHKG transcends its role as a mere data repository, emerging as a sophisticated and integrated knowledge representation framework capable of encapsulating a wide spectrum of health-related information. This includes, but is not limited to, diagnostic information, medication regimes, laboratory results, sensor-derived data, lifestyle parameters, and subjective patient experiences. The comprehensive nature of the PHKG makes it an invaluable resource for underpinning simulations and analyses within the digital twin framework, enabling a nuanced and holistic understanding of the patient's health dynamics.

3.2.4. Digital Twin Generation

The generation of a digital twin for each patient is a sophisticated process that harnesses the depth and breadth of the data encapsulated within the personal health knowledge graph (PHKG). This rich repository of semantically structured health data forms the bedrock upon which the digital twin is constructed, enabling a dynamic and personalized virtual representation of each patient's health status.

The digital twin employs advanced simulation models that are meticulously calibrated using comprehensive data derived from the PHKG. These models can simulate various physiological and metabolic processes relevant to the patient's condition, providing a virtual environment in which the consequences of different interventions can be explored. The simulation models are designed to mimic the patient's response to various treatments, lifestyle modifications, and potential disease-progression pathways. This allows healthcare providers to visualize the potential outcomes of different therapeutic strategies, facilitating informed decision making and personalized care planning. Moreover, the models can simulate the long-term implications of these interventions, aiding in the prevention and management of potential complications.

In parallel, the digital twin leverages machine learning algorithms that are trained on the heterogeneous and comprehensive dataset provided by the PHKG. These algorithms are adept at uncovering complex patterns within the data, including subtle correlations between various health indicators, treatment responses, and environmental or lifestyle factors [Beu 2022]. By analyzing these patterns, the algorithms can generate predictive insights into the patient's future health trajectory, identify risk factors for disease progression, and suggest preemptive measures to mitigate these risks.

The digital twin's machine learning component is not static; it continuously evolves as new data are incorporated into the PHKG, ensuring that the twin remains up to date with the patient's current health status and the latest medical knowledge. This dynamic learning process enhances the precision of the digital twins' predictions and recommendations, making them increasingly personalized and accurate over time.

3.3. Use Cases of GlycoTwin, Digital Twin for Diabetes Management

The Digital Twin, with rich data integration and simulation power offers several benefits and advantages for diabetes management, realized by (but not limited to) the following use cases:

3.3.1. Personalized Blood Glucose Regulation [Sar 2023]

- **Digital Twin's Role:** The digital twin provides historical patient data and a simulation environment to train and test insulin optimization strategies.
- **Algorithms:** Reinforcement learning (RL), specifically the Soft Actor–Critic (SAC) algorithm, refines insulin dosages with its entropy-driven reward function. The SAC algorithm balances precision with safe exploration to find optimal solutions for the individual.
- **Outcomes:** The digital twin enables personalized, data-driven insulin optimization, enhancing blood glucose control while reducing risks like hyperglycemia and hypoglycemia. Our method's efficacy was assessed based on three parameters: blood glucose concentration, the likelihood of experiencing hypoglycemia or hyperglycemia, and the duration within the

euglycemic zone (70–180 mg/dL), which is considered the ideal blood glucose interval to reduce diabetes-related complications. The outcomes indicated that our approach effectively maintained blood glucose within the desired range, reducing the risk of extreme fluctuations and increasing the time spent in the euglycemic zone. This demonstrates the power of digital twins to drive individualized care. **Figure 3** demonstrates the application of Soft Actor–Critic (SAC)-based reinforcement learning (RL) on a patient’s digital twin to enhance glucose level regulation, aiming to minimize the percentage of time that blood glucose level is in the risk range and stabilize overall glucose levels.

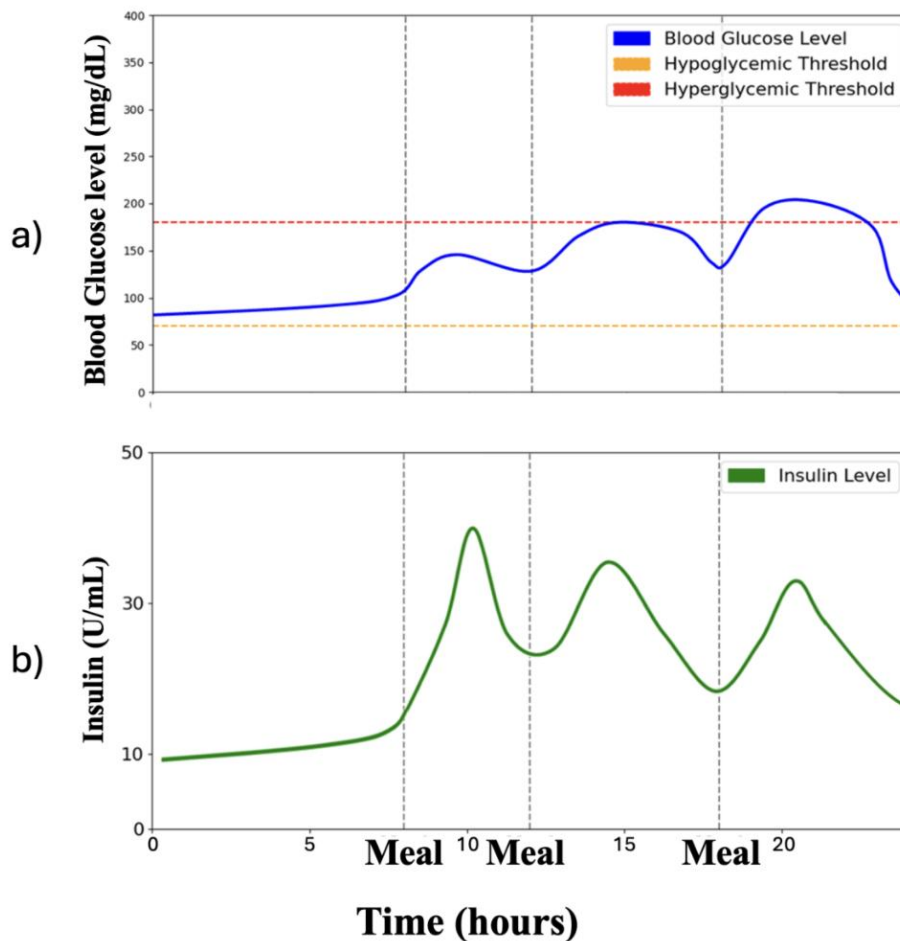


Figure 3. Optimized insulin dosage and resulting blood glucose control.
 (a) Simulated blood glucose trajectory under personalized insulin regimen.
 (b) Insulin doses are determined by the digital twins trajectory under personalized and administered after each meal.

3.3.2. Glucose Prediction for Individualized Care [Yan 2023]

- **Digital Twin’s Role:** The digital twin framework provides a structured dataset that integrates critical patient-specific factors such as glucose trends, food intake, insulin usage, and more. This comprehensive dataset is pivotal for the development and training of effective predictive models.

- **Algorithms: Recurrent Neural Networks (RNNs)** are ideal for analyzing time-series data within the digital twins. These networks identify complex patterns in individual glucose trajectories.
- **Outcomes:** The predictive models powered by the digital twins generate individualized glucose forecasts, enabling proactive care adjustments. These personalized predictions assist both patients and healthcare providers in making informed decisions to maintain blood glucose levels within the optimal range. As depicted in **Figure 4**, we integrated RNNs with our digital twins to predict glucose values, achieving an average **Root Mean Square Error (RMSE)** of 19.83 mg/dL, which signifies the models' precision based on the digital twins' data. This indicates a high level of accuracy in glucose prediction, which is critical for effective diabetes management. This metric reflects the model's ability to provide reliable forecasts that can be used in clinical settings.

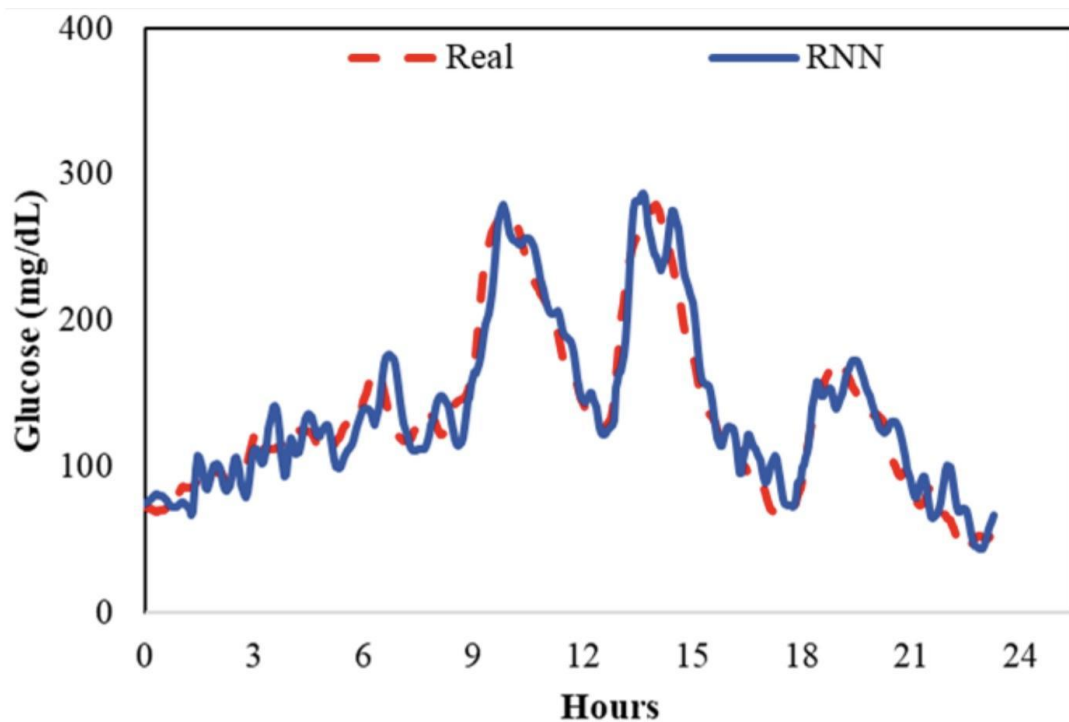


Figure 4. GlycoTwin: Digital Twin for blood glucose prediction

Figure 5 displays information gathered over a span of 10 days for an adult patient, showing their glucose, insulin, and carbohydrate (CHO) levels at 3 min intervals. Glucose levels are indicated on the left axis, while insulin and CHO levels are on the right. CHO values remain at zero except during mealtimes, and insulin levels remain stable until after meals when additional insulin is administered to manage glucose levels. The figure showcases the patient's use of self-designed food intake and time inputs, enabling the digital twin to monitor glucose levels and adjust interventions accordingly. The Digital Twin offers continuous monitoring and personalized interventions based on real-time data. Moreover, it allows for detailed examination of

daily or hourly data, as demonstrated by the data from day 5 to day 6 within a 24-hour timeframe.

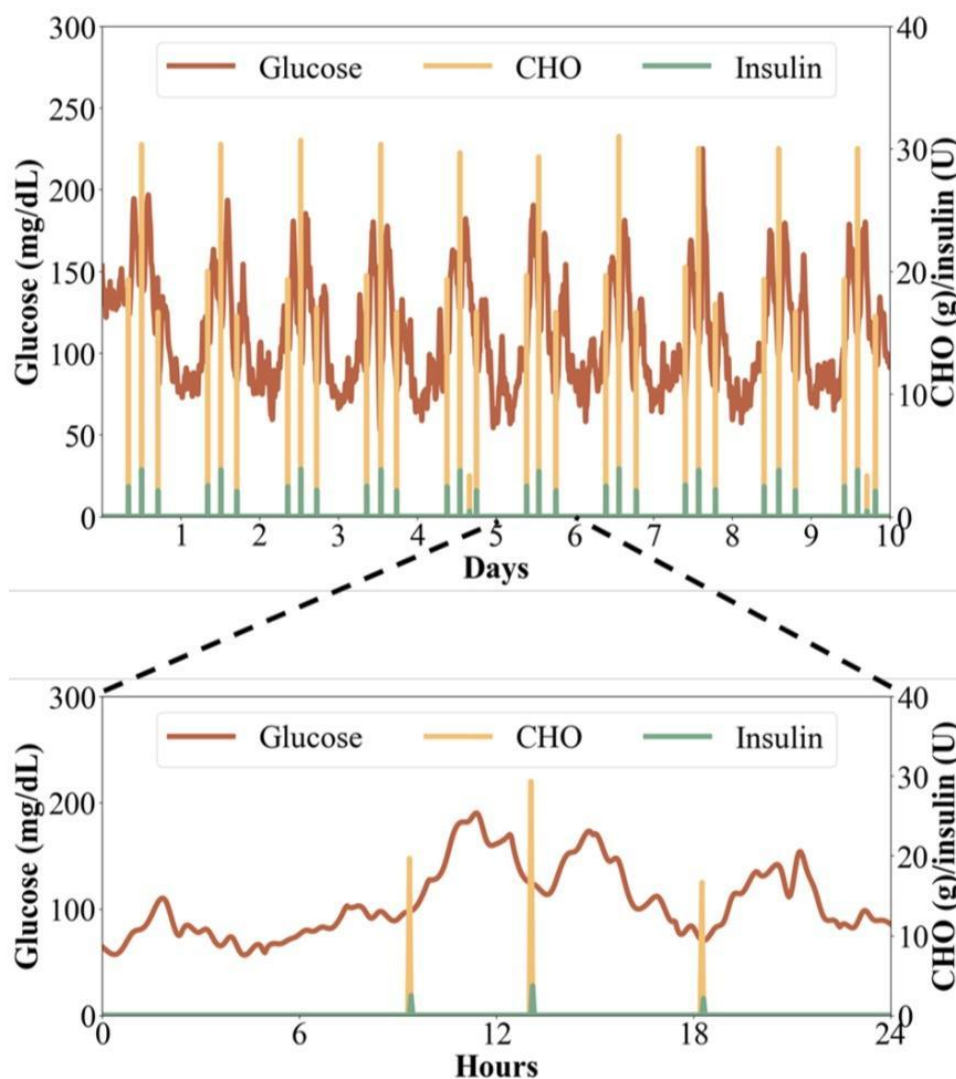


Figure 5. GlycoTwin: Digital Twin for data visualization (For monitoring of glucose, insulin, and carbohydrate (CHO) levels)

3.3.3. Healthcare Data Digital Twin Explorer [Hen 2024]

- **Digital Twin's Role:** The structured PHKG and its rich relationships between health concepts form the core of this application.
- **Interaction Modes:** As shown in **Figures 6(a) and 6(b)**, two interfaces provide flexibility:
 1. **Keyword Search:** Natural language processing converts user queries into SPARQL for knowledge graph retrieval. Semantic links offer further exploration avenues.
 2. **Navigation Interface:** Dropdown trees and graph visualizations allow users to explore the PHKG's hierarchy.

- **Outcomes:** The digital twin serves as a powerful tool for patients, granting them the ability to comprehend their health data independently and at their own pace. This empowerment in data literacy is instrumental in fostering patient engagement and active participation in collaborative care processes. Moreover, this highlights the digital twin’s potential to enhance patient-centered care by providing a user-friendly platform for health data exploration.

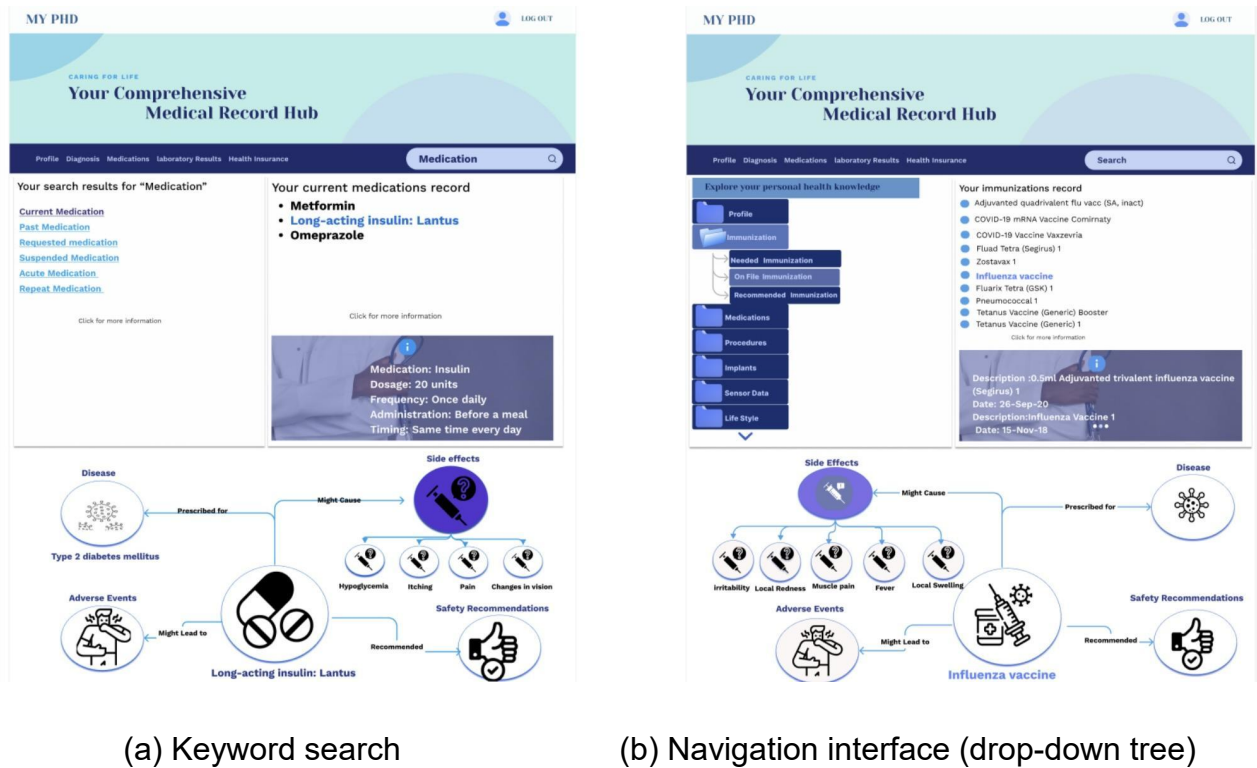


Figure 6. GlycoTwin: Digital Twin for health data explorer.

3.3.4. Personalized Meal Recommendation [Ami 2023]

- **Digital Twin’s Role:** The PHKG integrates information about a patient’s health condition, diabetes management plan, dietary preferences, and allergies. This comprehensive data profile fuels the meal recommendation engine.
- **Logic Rules and Reasoning:** Embedded within the knowledge graph are rules that reason about the patient’s health data and generate personalized meal suggestions. For example, rules might suggest meals that meet specific calorie goals, avoid allergens, and align with diabetes management guidelines.
- **Outcomes:** Our digital twin extends its capabilities beyond mere data provision; it delivers practical, personalized dietary recommendations that cater to each individual’s unique needs. This enables patients to make well-informed food selections that help regulate their blood sugar levels and enhance their overall health. As demonstrated in **Figure 7**, we have

developed a mobile application that leverages our digital twin to offer individualized meal suggestions for patients with diabetes.

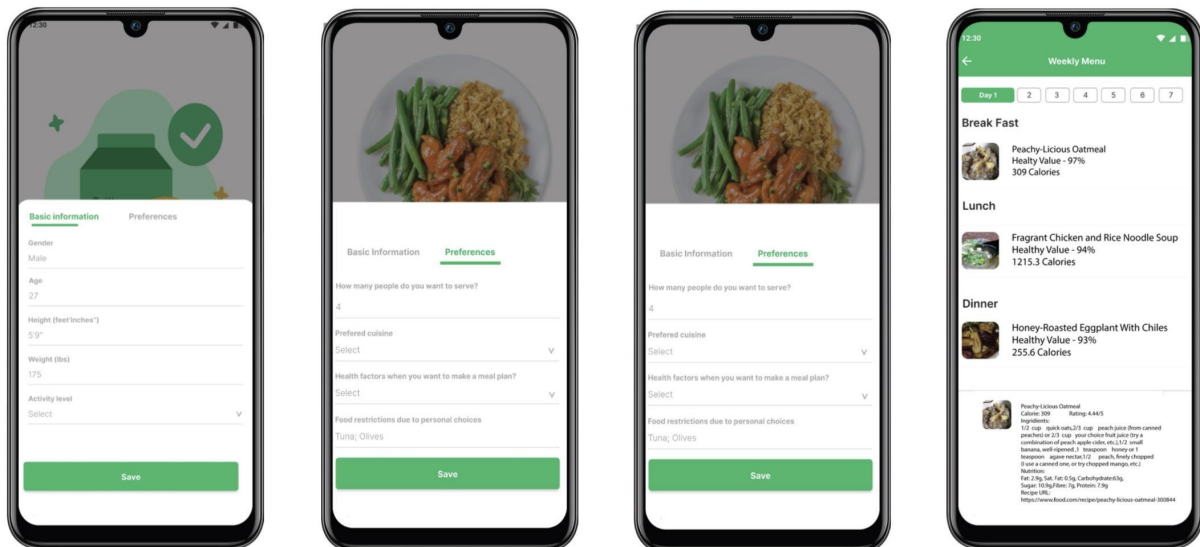


Figure 7. GlycoTwin: Digital Twin for personalized meal recommendations

3.4. Summary of Benefits, Challenges and Future Directions of Digital Twin for Diabetes Management

3.4.1. Benefits

1. **Personalized Medicine:** The AI Digital Twin (or Digital Twin for short) enables personalized diabetes management by simulating individualized glucose dynamics and predicting treatment outcomes.
2. **Improved Glucose Control:** The Digital Twin optimizes insulin dosing and medication adjustments, leading to improved glucose control and reduced risk of hypoglycemia and hyperglycemia.
3. **Enhanced Patient Engagement:** The Digital Twin empowers patients to take an active role in their diabetes management, providing personalized insights and recommendations for lifestyle modifications.
4. **Reduced Healthcare Costs:** The Digital Twin reduces healthcare costs by minimizing the need for hospitalizations, emergency department visits, and other costly interventions.

3.4.2 Technical Requirements and Challenges

The development and implementation of an Digital Twin for diabetes management require several technical requirements and pose challenges, including:

1. **Data Quality and Integration:** The Digital Twin requires high-quality, integrated data from various sources, including EHRs, CGMS, insulin pumps, and wearable devices.
2. **Physiological Modeling and Simulation:** The Digital Twin requires accurate and robust physiological models to simulate glucose dynamics and predict treatment outcomes.
3. **AI and ML Algorithm Development:** The Digital Twin requires the development and training of AI and ML algorithms to analyze data, identify patterns, and make predictions.
4. **Interoperability and Scalability:** The Digital Twin requires interoperability with various healthcare systems and devices, as well as scalability to accommodate large numbers of patients and data.

3.4.3. Future Directions

The AI Digital Twin for diabetes management is a rapidly evolving field, with several future directions and opportunities, including:

1. **Integration with Wearable Devices and Mobile Health Applications:** The AI Digital Twin can be integrated with wearable devices and mobile health applications to provide real-time glucose monitoring and personalized recommendations.
2. **Development of Closed-Loop Systems:** The AI Digital Twin can be used to develop closed-loop systems that automate insulin dosing and glucose control.
3. **Expansion to Other Chronic Diseases:** The AI Digital Twin can be applied to other chronic diseases, such as hypertension, cardiovascular disease, and chronic kidney disease.
4. **Development of Explainable AI and Transparency:** The AI Digital Twin requires the development of explainable AI and transparency to ensure that patients and healthcare providers understand the decision-making process and recommendations.

4. Digital Twin for Inner Engineering - A Perspective

The ultimate goal of human beings is to elevate wisdom and sustain good health. We have discussed the application of Digital Twin in healthcare, specifically in diabetes management. In this section, we provide a glimpse on how Digital Twin can be used in elevating wisdom, via so-called **inner engineering**. The construction process of Digital Twin for healthcare is essentially similar to the one for inner engineering for wisdom development.

4.1 Concepts and Background of Inner Engineering

Inner Engineering is a comprehensive framework for personal growth, self-awareness, and spiritual evolution, developed by **Sadhguru**, a renowned Indian yogi, mystic, and author. Inner engineering is a scientific approach to exploring the human interior, enabling individuals to engineer their inner world and transform their lives, through cultivation of the following:

- **Self-Awareness:** Understanding and being aware of one's thoughts, emotions, and actions.
- **Consciousness:** Awareness of the present moment, thereby developing wisdom and high-level of consciousness.
- **Energy:** Balancing and optimizing one's physical, mental, and emotional energy, thereby cultivating pure energy from within to be in tune with the central energy of the universe.
- **Spirituality:** Exploring the higher dimensions of human existence, beyond the physical dimension, by reaching the state of complete equilibrium, serenity and nothingness.

Fundamentally, inner engineering targets wisdom (or super consciousness) development, which requires a multidimensional approach that incorporates spiritual practices, self-inquiry, and lifestyle changes. Here are some key steps in inner engineering:

4.1.1 Spiritual Practices

- **Meditation:** Regular meditation practice helps quiet the mind, increases self-awareness, and expands consciousness.
- **Prayer or Mantra Repetition:** Focus on a higher power or a personal mantra that can be invoked vocally or silently to create spiritual vibrations to cultivate a sense of connection and inner peace.
- **Yoga, Qigong or KiDao:** combines physical postures, breathing techniques, and meditation to balance the body, mind, and spirit.

4.1.2 Self-Inquiry and Reflection

- **Journaling:** Record your thoughts, emotions, and insights to identify patterns, gain clarity, and develop self-awareness.
- **Self-Reflection:** Schedule regular time for introspection, asking yourself questions like "What am I grateful for?" "What can I improve?" or "What is my purpose?". With perseverant mantra invocations and spiritual practice, self-reflection will become instantaneous.
- **Seek Feedback:** Engage with mentors, coaches, or trusted fellow friends to share spiritual experience and gain new perspectives and insights.

4.1.3 Lifestyle Changes

- **Nature Connection:** Spend time in nature to cultivate a sense of awe, wonder, and interconnectedness.
- **Healthy Habits:** Establish a balanced lifestyle, including regular exercise, wholesome nutrition, and sufficient sleep.
- **Mindful Relationships:** Nurture relationships that support your growth, and practice empathy, compassion, and active listening.

4.1.4 Intellectual and Creative Pursuits

- **Lifelong Learning:** Engage in continuous learning, exploring subjects that fascinate you, such as philosophy, psychology, or spirituality.
- **Creative Expression:** Pursue creative activities, like art, music, writing, or dance, to tap into your inner world and express yourself authentically.

4.1.5 Energetic and Vibrational Alignment

- **Energy Healing:** Explore modalities like Taichi, Vovi, acupuncture, or sound healing to balance and align your energy.
- **Vibrational Resonance:** Surround yourself with positive influences, such as uplifting music, inspiring books, or supportive community.

4.1.6 Patience and Persistence

- **Cultivate Patience:** Recognize that developing wisdom and super consciousness is a lifelong journey, requiring patience, dedication, and self-compassion.
- **Embrace Challenges:** View challenges and setbacks as opportunities for growth, learning, and self-refinement.

Needless to say, the path to wisdom and super consciousness is unique to each individual. Therefore, constructing individual Digital Twin for wisdom elevation management will be essential for inner engineering. In the same way of constructing a Digital Twin for healthcare, we should create a Digital Twin for inner engineering using the same framework and the prescribed practice of inner engineering.

4.2 On the Construction of Digital Twin for Inner Engineering

The construction of Digital Twin for inner engineering should be analogous to the one for diabetes management or healthcare. Some general points are highlighted in this section, while detailed research is still ongoing.

4.2.1. Ontology Development

This wisdom-related spirituality ontology needs to be intricately designed to offer a comprehensive vocabulary and articulate the complex relationships inherent within the spiritual domain, acting as the structural foundation upon which the digital twin models are constructed. The vocabulary would be a refined subset of the union of

all terminologies of all religions, as well as the cognitive para-psychology and part of the neuroscience. This ontology development methodology is expected to adopt a systematic, top-down structure analogous to the one in the healthcare domain. For example, the “Wisdom” concept can have different levels of advancement such as: 1) Ultimate Wisdom, 2) Spiritual and Divine Realms, 3) Energy (Chakras) Realm, 4) Human and Individual Development, 5) Spiritual Growth and Development, 6) Intellectual and Knowledge Development. These are divided into object properties, which connect different concepts within the ontology, and data properties, which link concepts to specific values, facilitating a detailed and relational representation of spirituality data.

4.2.2. Data Collection and Integration

The approach to data collection and integration is expansive and meticulous. We should gain access to various static and dynamic spirituality data sources, including but not limited to church record of the person, historical record, school records, electronic health records (EHRs), social media records of interactions, inputs from wearable devices, daily online recorded activities, and direct personal-generated data, including journals. Thus the digital “akashic” record is dynamically created and maintained. Each of these sources plays a pivotal role in painting a comprehensive picture of an individual state of spiritual advancement, offering unique insights that are integral to the construction of a detailed and accurate digital twin. So, a broad dataset including all personal actions and inner states should be recorded.

4.2.3. Personal Spiritual Knowledge Graph (PSKG) Construction

The construction of the personal spiritual knowledge graph (**PSKG**) is a critical phase that follows the meticulous integration and transformation of spirituality data. This pivotal transformation marks the transition of raw spirituality data into a structured format that is amenable to semantic querying and reasoning, laying the groundwork for the robust instantiation of the knowledge graph. The PSKG is sculpted based on the intricacies of the predefined ontology, serving as a dynamic representation of the individual state of spiritual advancement.

4.2.4. Digital Twin Generation for inner engineering

The generation of a digital twin for each individual is a sophisticated process that harnesses the depth and breadth of the data encapsulated within the personal spirituality knowledge graph (PSKG). This rich repository of semantically structured spiritual data forms the bedrock upon which the digital twin is constructed, enabling a dynamic and personalized virtual representation of each person’s spiritual status. The digital twin employs advanced simulation models that are meticulously calibrated using comprehensive data derived from the PSKG.

These models can simulate various physiological and metabolic processes relevant to the patient's condition, providing a virtual environment in which the consequences of different interventions can be explored. The simulation models are designed to mimic the patient's response to various treatments, lifestyle modifications, and potential disease-progression pathways. This allows healthcare providers to visualize the potential outcomes of different therapeutic strategies, facilitating informed decision making and personalized care planning. Moreover, the models can simulate the long-term implications of these interventions, aiding in the prevention and management of potential complications.

In parallel, the digital twin leverages machine learning algorithms that are trained on the heterogeneous and comprehensive dataset provided by the PHKG. These algorithms are adept at uncovering complex patterns within the data, including subtle correlations between various health indicators, treatment responses, and environmental or lifestyle factors. By analyzing these patterns, the algorithms can generate predictive insights into the patient's future health trajectory, identify risk factors for disease progression, and suggest preemptive measures to mitigate these risks.

The digital twin's machine learning component is not static; it continuously evolves as new data are incorporated into the PHKG, ensuring that the twin remains up to date with the patient's current health status and the latest medical knowledge. This dynamic learning process enhances the precision of the digital twins' predictions and recommendations, making them increasingly personalized and accurate over time.

4.3 Ideas of a Digital Twin Model for Inner Engineering

Developing a viable Digital Twin model for Inner Engineering is a major undertaking. In this section, we present a preliminary illustrative example for constructing a Digital Twin for Inner Engineering, based on the principle of ontology described in the previous (sub)subsections.

- **Components of the Digital Twin**

1. *Individual Profile*: A comprehensive profile of the individual, including physical, emotional, mental, and spiritual characteristics.
2. *Mind Model*: A dynamic model of the individual's mind, incorporating their thoughts, emotions, and behaviors.
3. *Energy System*: A model of the individual's energy system, including their chakras, aura, and energy flows.
4. *Spiritual Growth Model*: A model of the individual's spiritual growth and development, incorporating their values, beliefs, and spiritual practices.
5. *Environmental Factors*: A model of the individual's environment, including their social, cultural, and physical surroundings.

- **Data Sources**

1. *User Input*: The individual will provide input on their thoughts, emotions, behaviors, and spiritual practices.
2. *Wearable Devices*: Wearable devices such as smartwatches, fitness trackers, and EEG headbands will provide data on the individual's physical and emotional states.
3. *Mobile Apps*: Mobile apps such as meditation and mindfulness apps will provide data on the individual's spiritual practices and progress.
4. *Social Media*: Social media platforms will provide data on the individual's social interactions and environmental factors.

- **Analytics and Insights**

1. *Pattern Recognition*: The Digital Twin will recognize patterns in the individual's thoughts, emotions, behaviors, and spiritual practices.
2. *Predictive Analytics*: The Digital Twin will use predictive analytics to forecast the individual's future states and outcomes.
3. *Personalized Recommendations*: The Digital Twin will provide personalized recommendations for the individual's spiritual growth and development.

- **Benefits**

1. *Improved Self-Awareness*: The Digital Twin will provide the individual with a deeper understanding of their thoughts, emotions, behaviors, and spiritual practices.
2. *Enhanced Spiritual Growth*: The Digital Twin will provide personalized recommendations for the individual's spiritual growth and development.
3. *Better Decision-Making*: The Digital Twin will provide the individual with predictive analytics and insights to inform their decision-making.

- **Technical Requirements**

1. *Cloud Infrastructure*: A cloud-based infrastructure will be required to store and process the individual's data.
2. *Artificial Intelligence*: Generative AI and deep machine learning algorithms, including the use of AI agents will be required to analyze the individual's data and provide personalized recommendations.
3. *Data Visualization*: Data visualization tools will be required to provide the individual with a user-friendly interface to view their data and insights.

- **Security and Privacy**

1. *Data Encryption*: The individual's data will be encrypted to ensure confidentiality and security.
2. *Access Control*: Access to the Digital Twin will be restricted to authorized personnel and the individual themselves.
3. *Informed Consent*: The individual will provide informed consent for the collection and use of their data.

4.4 Metrics in the Digital Model

Here are some potential metrics that could be involved in the Digital Twin model for Inner Engineering:

- **Individual Profile Metrics**

1. *Emotional Intelligence (EI)*: A measure of the individual's self-awareness, self-regulation, motivation, empathy, and social skills.
2. *Personality Traits (PT)*: Metrics such as the Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism).
3. *Values and Beliefs (VB)*: A measure of the individual's core values and beliefs, such as spirituality, compassion, and fairness.

- **Mind Model Metrics**

1. *Thought Patterns*: Metrics such as thought frequency, thought duration, and thought content (e.g., positive, negative, neutral).
2. *Emotional States*: Metrics such as emotional intensity, emotional duration, and emotional frequency (e.g., happiness, sadness, anger).
3. *Mindfulness*: Metrics such as mindfulness frequency, mindfulness duration, and mindfulness quality (e.g., focused attention, open monitoring).
4. *Love (L)*: A measure of the individual's level of love, compassion, and kindness towards themselves and others.
5. *Wisdom (W)*: A measure of the individual's level of wisdom, insight, and discernment.
6. *Courage (C)*: A measure of the individual's level of courage, perseverance, and resilience.

- **Energy System Metrics**

1. *Chakra Balance*: Metrics such as chakra energy levels, chakra balance, and chakra alignment.
2. *Aura Quality*: Metrics such as aura color, aura clarity, and aura strength.
3. *Energy Flow*: Metrics such as energy flow rate, energy flow direction, and energy flow blockages.
4. *Astral and Soul Traveling*: Metrics of the individual's frequency of astral and soul traveling experiences.

- **Spiritual Growth Model Metrics**

1. *Spiritual Practices*: Metrics such as practice frequency, practice duration, and practice quality (e.g., meditation, prayer, yoga).
2. *Spiritual Experiences*: Metrics such as experience frequency, experience duration, and experience intensity (e.g., feelings of connection, feelings of peace).
3. *Spiritual Values*: Metrics such as values alignment, values clarity, and values commitment (e.g., compassion, forgiveness, gratitude).
4. *Spiritual Balance Index (SBI)*: A composite measure of the individual's level of inner peace, love, wisdom and courage.

5. *Transcendence Quotient (TQ)*: A composite measure of the individual's level of transcendence of the ego and the material world, including their experience of nothingness and emptiness.

- **Environmental Factors Metrics**

1. *Social Connections*: Metrics such as social connection frequency, social connection duration, and social connection quality (e.g., supportive, nurturing, challenging).
2. *Physical Environment*: Metrics such as physical environment quality, physical environment safety, and physical environment comfort (e.g., natural light, air quality, noise level) [Beu 2022].
3. *Cultural and Societal Influences*: Metrics such as cultural and societal influence frequency, cultural and societal influence duration, and cultural and societal influence intensity (e.g., media consumption, social norms, cultural values).

These metrics can be used to track progress, identify areas for improvement, and provide personalized recommendations for spiritual growth and development.

5. Conclusions

In recent years, especially in 2024, we have seen a tremendous surge of research and development activities on AI in both the private and public sectors, in particular in the domains of Generative AI, AI Agents and Digital Twins. In this paper, we presented an overview of the state of the art of Digital Twins, with a ground breaking research of Digital Twins as applied to diabetes management, as an example. We also present some preliminary ideas on the construction of a Digital Model for Inner Engineering, for elevating wisdom and happiness, aiming at enhancing the quality of life. In the foreseeable future, we envisage that every human being will have multiple Digital Twins, supported by multiple AI agents, giving rise to billions of active Digital Twins in the cyberspace. These Digital Twins will communicate and interwork among themselves and with multiple AI agents to form the so-called Internet of Minds (IOM) transforming healthcare, spirituality, happiness and longevity in the Revolution 5.0. Physical human entities may die, but their existences in terms of Digital Twins, that carry their personal characteristics, can “live” forever, diminishing the boundaries between/among the earthly world and the multiverse.

References

[Ami 2023] Amiri, M.; Li, J.; Hasan, W. “Personalized Flexible Meal Planning for Individuals with Diet-Related Health Concerns: System Design and Feasibility Validation Study”. *JMIR Form Res.* 2023, 7, e46434.

[Apa 2021] L. Fregoso-Aparicio, J. Noguez, L. Montesinos, J.A. García-García “Machine learning and deep learning predictive models for type 2 diabetes: A systematic review” *Diabetol. Metab. Syndr.* 2021, 13, 148.

[Bac 2013] Backholer, K.; Peeters, A.; Herman, W.H.; Shaw, J.E.; Liew, D.; Ademi, Z.; Magliano, D.J. “Diabetes Prevention and Treatment Strategies: Are we doing enough?” *Diabetes Care* 2013, 36, 2714–2719.

[Beu 2022] Beulens, J.W.J.; Pinho, M.G.M.; Abreu, T.C.; den Braver, N.R.; Lam, T.M.; Huss, A.; Vlaanderen, J.; Sonnenschein, T.; Siddiqui, N.Z.; Yuan, Z.; et al. “Environmental risk factors of type 2 diabetes—An exposome approach”. *Diabetologia* 2022, 65, 263–274.

[Chu 2023] Chu, Y.; Li, S.; Tang, J.; Wu, H. “The potential of the Medical Digital Twin in diabetes management: A review”. *Front. Med.* 2023, 10, 1178912.

[Cro 2020] Croatti, A.; Gabellini, M.; Montagna, S.; Ricci, A. “On the Integration of Agents and Digital Twins in Healthcare”. *J. Med. Syst.* 2020, 44, 161.

[Das 2022] Das, C.; Mumu, A.A.; Ali, M.W.; Sarker, S.; Muyeen, S.M.; Das, S.K.; Das, P.; Hasan, M.M.; Tasneem, Z.; Islam, M.M.; et al. “Toward IoRT Collaborative Digital Twin Technology Enabled Future Surgical Sector: Technical Innovations, Opportunities, and Challenges”. *IEEE Access* 2022, 10, 129079–129104.

[Fel 2017] Feldman, A.L.; Long, G.H.; Johansson, I.; Weinehall, L.; Fhärm, E.; Wennberg, P.; Norberg, M.; Griffin, S.J.; Rolandsson, O. “Change in lifestyle behaviors and diabetes risk: Evidence from a population-based cohort study with 10 year follow-up”. *Int. J. Behav. Nutr. Phys. Act.* 2017, 14, 39.

[Har 2020] Harris, S.B.; Cheng, A.Y.; Davies, M.J.; Gerstein, H.C.; Green, J.B.; Skolnik, N. “Person-centered, outcomes-driven treatment: A new paradigm for type 2 diabetes in primary care”. *ADA Clin. Compend.* 2020, 2020.

[Hen 2024] Hendawi, R.; Li, J. “Comprehensive Personal Health Knowledge Graph for Effective Management and Utilization of Personal Health Data”. In *Proceedings of the IEEE Artificial Intelligence, Medicine, Health, and Care, Laguna Hills, CA, USA, 5–7 February 2024*.

[HL7 2023] “Health Level Seven International. HL7 FHIR (Fast Healthcare Interoperability Resources)”. HL7. 2023. Available online: <https://www.hl7.org/fhir/>

[Kam 2021] Kamel Boulos, M.N.; Zhang, P. “Digital twins: From personalised medicine to precision public health”. *J. Pers. Med.* 2021, 11, 745

[Kio 2019] Kiourtis, A.; Mavrogiorgou, A.; Menychtas, A.; Maglogiannis, I.; Kyriazis, D. Structurally Mapping Healthcare Data to HL7 FHIR through Ontology Alignment. *J. Med. Syst.* 2019, 43, 62.

[Ndj 2020] Ndjaboue, R.; Farhat, I.; Ferlatte, C.-A.; Ngueta, G.; Guay, D.; Delorme, S.; Ivers, N.; Shah, B.R.; Straus, S.; Yu, C.; et al. "Predictive models of diabetes complications: Protocol for a scoping review", *Syst. Rev.* 2020, 9, 137.

[Nye 2023] Nye, L. Digital Twins for Patient Care via Knowledge Graphs and Closed-Form Continuous-Time Liquid Neural Networks. *arXiv* 2023, arXiv:2307.04772.

[Ort 2022] Ortiz-Martínez, M.; González-González, M.; Martagón, A.J.; Hlavinka, V.; Willson, R.C.; Rito-Palomares, M. Recent Developments in Biomarkers for Diagnosis and Screening of Type 2 Diabetes Mellitus. *Curr. Diabetes Rep.* 2022, 22, 95–115

[Pes 2022] Pesapane, F.; Rotili, A.; Penco, S.; Nicosia, L.; Cassano, E. "Digital Twins in Radiology", *J. Clin. Med.* 2022, 11, 6533.

[Qin 2023] Qin, H.; Wang, C.; Li, Y.; Li, Z.; Wang, L. P-2.15: Status Quo and Future Development of Digital Twins in Medical and Health Fields. *Sid Symp. Dig. Tech. Pap.* 2023; 54, 533–536.

[Rad 2024] F. Rad, R. Hendawi, X. Yang and J. Li, "Personalized Diabetes Management with Digital Twins: A Patient-Centric Knowledge Graph Approach", *Journal of Personalized Medicine* 2024, 14, 359. <https://doi.org/10.3390/jpm14040359>

[Sar 2023] Sarani Rad, F.; Li, J. Optimizing Blood Glucose Control through Reward Shaping in Reinforcement Learning. In *Proceedings of the IEEE International Conference on E-Health Networking, Application & Services (HealthCom), Chongqing, China, 15–17 December 2023.*

[Sub 2014] Subramanian, S.; Hirsch, I.B. Personalized Diabetes Management: Moving from Algorithmic to Individualized Therapy. *Diabetes Spectr.* 2014, 27, 87–91.

[Sun 2022] Sun, T.; He, X.; Song, X.; Shu, L.; Li, Z. The Digital Twin in Medicine: A Key to the Future of Healthcare? *Front. Med.* 2022, 9, 907066.m

[Tha 2023] Thamocharan, P.; Srinivasan, S.; Kesavadev, J.; Krishnan, G.; Mohan, V.; Seshadhri, S.; Bekiroglu, K.; Toffanin, C. Human "Digital Twin for Personalized Elderly Type 2 Diabetes Management". *J. Clin. Med.* 2023, 12, 2094.

[Tur 2023] Turab, M.; Jamil, S. A Comprehensive Survey of Digital Twins in Healthcare in the Era of Metaverse. *BioMedInformatics* 2023, 3, 563–584.

[Yan 2023] Yang, X.; Li, J. Edge AI Empowered Personalized Privacy-Preserving Glucose Prediction with Federated Deep Learning. In *Proceedings of the IEEE International Conference on E-Health Networking, Application & Services (HealthCom), Chongqing, China, 15–17 December 2023.*

[Yi 2023] Yi, H. Improving cloud storage and privacy security for digital twin based medical records. *J. Cloud Comput.* 2023, 12, 151.

[Zot 2023] Zoltick, M.M.; Maisel, J.B. Societal Impacts: Legal, Regulatory and Ethical Considerations for the Digital Twin. In *The Digital Twin*; Crespi, N., Drobot, A.T., Minerva, R., Eds.; Springer International Publishing: Cham, Switzerland, 2023; pp. 1167–1200.