# Human Digital Twin with Applications

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## ABSTRACT

The concept formation of Human Digital Twin (HDT), including basic considerations, construct of HDT, and the features of HDT is presented in this paper. The steps and methods for HDT construction are described, which include template human model creation, human model unification, individualization, data links with data driven models, and integration. Two projects where HDT are used for practical problems are introduced.

## 1. INTRODUCTION

A 'Digital Twin' is a virtual representation or digital form of a physical object or process in the real world. The digital twin technology has been widely implemented by industry in recent years (Grieves 2021). As the real world is centered around the human, the digital representation or virtual self of the human should be at the center of the digital world. This basic consideration motivated the concept and technology of the Human Digital Twin (HDT) developed at Innovision since 2017 (Cheng 2019). The HDT developed by Innovision is based on individualized human models combined with personal data containers linked to sensors. The data can be processed using analytics to provide an integrated, dynamic representation of one's personal physical and physiological states. Combined with physics solvers, a HDT can be used to perform physics-based analysis, simulation, and prediction of physical and physiological performance of an individual (Cheng et al., 2020).

This paper presents the development of HDT technology, including concept formation, construction, potential applications, current limitations, and prospects. As practical examples of HDT applications, two funded projects are introduced, where patient digital twin is used to improve the compliance of Physiotherapy Scoliosis Specific Exercises (PSSEs) and pilot digital twin is used to mitigate the acute neck injury and chronic neck pain of military pilots, respectively.

## 2. HDT CONCEPT FORMATION

### 2.1 Basic Considerations

1) Traditional human models have two major limitations: (a) Each describes a single aspect or small set of human features/characteristics; and (b) They typically describe the average properties of a human. Often, one model is used to represent a group or population. Humans, however, embody a complicated system with distinct characteristics ranging from physical, biological, and physiological features to cognitive and behavioral traits. Though a complete digital representation of human is still far from reality, a unified representation of multiple features of human with a high level of details and fidelity is possible due to rapid advancement of digital human modeling and computer technology in recent years. Conventionally, human body shape (with anthropometry), musculoskeletal characteristics, and anatomy are described separately by three independent models with different data representations. However, human features/characteristics are inter-dependent. It is advantageous that they be described in a unified way, if possible, so that the unification can more accurately describe a human. Particularly, human body shape, musculoskeletal characteristics, and anatomy all embody human physical features and lend themselves to the unified modeling.
2) Humans share common gender-specific anatomy and gross physical attributes. Therefore, we can create a unified model structure and data structure and standard models (templates) that can be used for all

humans. Humans' differences make each of us unique and differentiated from others in anthropometry, race, ethnicity, biomechanical, metabolic, and physiologic attributes. This motivates the creation of individualized human models.

3) Creating a digital human model for an individual requires a large amount of work as more individual details are included. To keep the effort tractable and affordable, one can use standard models as templates and then create individualized (instance) models from the template models via fitting, morphing, and scaling based on the personal data. In this fashion, the individualized models will provide a representation of the person, with the level of details and medical fidelity that is sufficient for the intended applications.
4) In special applications as joint replacement and augmented reality assisted surgery, the regional models of particular parts of body or tissue groups can be created from the actual data of that person (e.g., Magnetic Resonance Imaging (MRI) data, and X-ray Computed Tomography (CT) data, etc.) so that a higher level of anatomical details and medical fidelity is attained.
5) Some human physical and biological features are not suitable to be represented by a static model and their states need to be updated frequently. Therefore, we use data containers to store and manage these data and data-driven models to describe these features and states.
6) As an approximate representation of a real human, HDT is far from a complete digital replica of human. As digital human modeling technology advances, more models of human physical and psychological characteristics (e.g., cognitive, behavioral, and bio-physics models) will become technically feasible. The structure of our HDT is open, allowing these human models to be integrated in the future.

**2.2 Construct of HDT**

As shown in Figure 1, HDT comprises individualized and unified human models combined with personal data containers with data analytics. We incorporate and integrate three different models:

1) 3D Human body shape model with anthropometry, which provides a complete 3D surface mesh description of human body shape along with anthropometric measurements.
2) Full body musculoskeletal model, which includes skeletal geometry, rigid linkage with multiple degrees of freedom to define joint kinematics, and Hill-type models of muscles and tendons. This provides a non-invasive means to study human kinematics and movement.
3) Full body finite element model, which uses solid finite element meshes to describe the complete anatomical structure of the human body in terms of tissue groups.

Other models, such as a human behavior model, lifestyle model, and cognitive model will be explored and evaluated in the future. They will be integrated into the unified framework when they become technically mature. These models, each of which describes specific human aspects, are integrated into a framework having unified model and data structures. This framework facilitates the sharing of common data and functional information exchange among model elements. These elements remain the same for every individual. The state-of-the-art standard models are used as the templates for the individualized models.

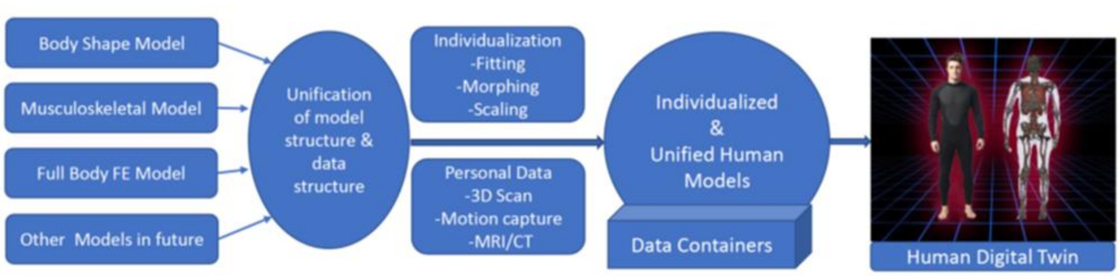



Figure 1. An overview of Human Digital Twin.

An individualized model is created from the template models via morphing and fitting that is appropriate for the individual. The personal data to be used includes the 3D body scan, motion capture data, MRI data, and X-ray data, each of which provides different levels of details of body.

Data containers are linked to wearable sensors, ambient environmental conditions, and other data sources. Data containers are used to store and manage the personal data of physical, physiological, and cognitive status, health data, activity tracking data, and medical treatment data. These data can be used to establish predictive alerts and guide people to healthier lifestyles (Bruynseels et al., 2018). Moreover, data-driven models (e.g., empirical regression models and deep neural network models) can be created from these data (Brunton and Kutz, 2019).

### 2.3 Features of HDT

The unique feature of HDT can be summarized as follows.

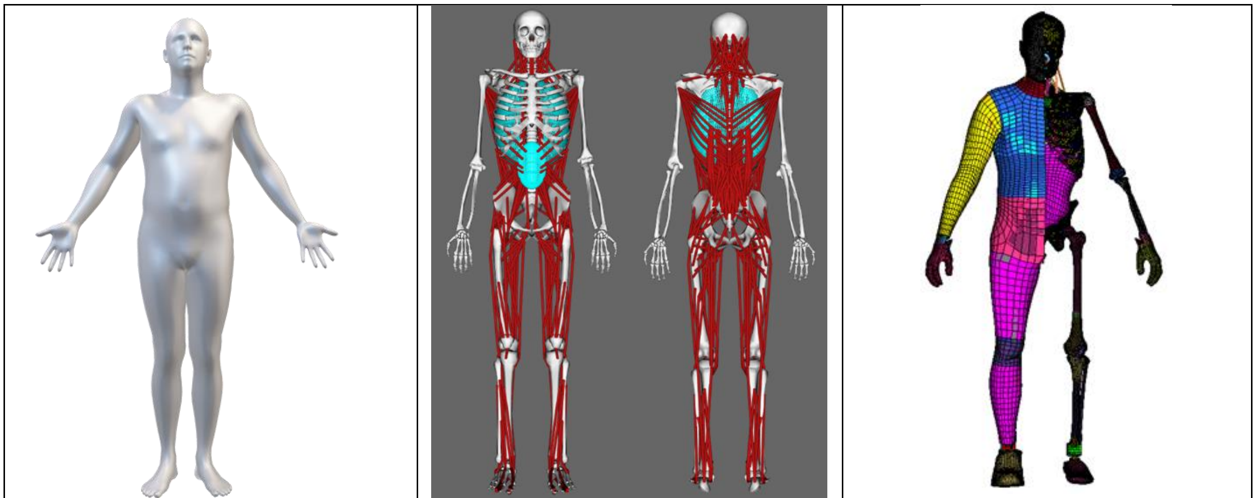
1) **Physics or first principle based:** HDT is created based on the physics and/or first principles of anthropometrics, biomechanics, physiology, biology, behavioral and cognitive sciences. Integrated with physics solvers, HDT can be used to analyze and simulate personal physical and physiological responses and status.
2) **Individualized**: HDT contains individualized human models, which are created based on the personal data, thus providing fair description of the unique features/characteristics of an individual.
3) **Unified**: Different types of human model are integrated into a unified framework with unified model structure and data structure. The unification leads to more effective and coherent representation of various features/characteristics of human and promotes synergetic utilization of different models.
4) **Quick generation:** The state-of-the-art standard models are used as the template models. The individualized models are then created from the template models by means of fitting, morphing, scaling, and other methods based on the personal data. As such, one can quickly build individualized models with tractable efforts and at the same time provide sound approximate representation of an individual.
5) **Dynamic**: Data containers are linked to wearable sensors or other data sources, so that the parameters, features, and states of HDT will be updated at different time scales which are appropriate for respective human features/characteristics.
6) **Progressive**: HDT has an open structure, allowing for new human models to be integrated when they are technically feasible.
7) **Flexible**: The level of details and bio-fidelity of the models is flexible, depending on the intended uses and data availability. Whereas the base models are intended to meet basic requirements for common applications, the refined and enhanced models can meet more stringent requirements for special applications.
8) **Affordable:** The individualized models are created from the templates via individualization. As such, the effort to build individual models becomes tractable and affordable. This is crucial to a variety of applications where cost matters.

## 3. HDT CONSTRUCTION

The process for HDT construction includes template model creation, model unification, and individualization. The methods used in these steps are described as follows.

### 3.1 Template Model Creation

Various methods have been developed for creating static and dynamic human shape models (Cheng and Robinette, 2009), including deriving 3D body shape models from 2D imagery via deep learning (Dibra et al, 2017). We use the parameterized human shape model developed (Figure 2(a)) as the template for human shape modeling. This template model, which can be gender-specific, is fit to the 3D body scan of an individual to generate a body shape model. Point-to-point surface registration methods, such as coherent point drift (Myronenko and Song, 2009), can be used to fit the template model to the target scan surface via non-rigid registration. By this approach, point-to-point correspondence will be established between the template model and an individual model and among all individual models.



(a) Shape model | (b) Musculoskeletal model | (c) Full body FE model

Figure 2. Template models for creating individual models.

Full body musculoskeletal models are of great interest due to their ability to provide a more accurate representation of human motion. Under Dynamic Avatars with Complete Articulated Anatomy (DACAA) (Cheng et al., 2020), a small business innovative research Phase I and Phase II program sponsored by the Defense Health Agency, a full body musculoskeletal model (Figure 2(b)) was developed by combining previously validated OpenSim (Delp et al., 2007) (https://simtk.org) models, including the full body lumber spine model (Raabe and Chaudhari, 2016), the musculoskeletal model for spinal injuries (Cazzola et al., 2017), and the upper extremity model (Saul et al., 2015). We can use this model as the template for all individual musculoskeletal models.

Full body finite element models have advanced significantly for the past decade as an important tool for assessing protection for humans exposed to dynamic events. In DACAA, we have developed a framework to convert an Individual Avatar with Complete Anatomy (IAVCA) developed by Zientara and Hoyt (2017) at the US Army Research Institute of Environmental Medicine (USARIEM) to a fully functional full body finite element model, as shown in Figure 2(c). We can use this model as the template model for all individual full body finite element models.

### 3.2 Human Model Unification

Human body shape, musculoskeletal system, and internal anatomical structures represent different human physical features. Yet, these are inter-related features. The unification of different types of models used to represent these features leads to a more coherent representation of various aspects of human features and characteristics. The unification promotes (a) sharing of common data; (b) exchanging/transferring information between different models; (c) synchronizing the status of different models; and (d) working together to provide more capabilities for analysis and prediction.

Contributing factors supporting model unification include: (a) Surface (skin) landmarks can be used to determine joint centers for the musculoskeletal model and bony structural features; (b) The inertial properties of body segments can be approximately determined using full body finite element model based on the body shape model; (c) An injury to or a surgery on the body can affect the body shape, anatomical structure, and musculoskeletal simultaneously; and (d) The musculoskeletal model can be used to predict a person's motion, while the full body finite element model can be used to predict the stress in a body region per frame (in an animation). The predictions from both models can then be input for a physiology engine to predict one's physiological states and vital signs (e.g., metabolic energy consumption, heart rate, breath rate, etc.).

### 3.3 Individualization

Human digital twin is a virtual rendition of an individual with all human characteristics. This requires all the technical means available for individualization. Individual model can be created one for one based on personal data, but a significant effort is required to build a model from scratch. Given potential applications of HDTs, if a large number of HDTs are created, the modeling effort may become intractable. To ensure the feasibility of creating HDTs, one can create the models for an individual via individualization which generates instance (individual) models from the template models by fitting, morphing, and scaling, as shown in Figure 3.

- Fitting: To create an individualized shape model, we fit a template shape model to the 3D full body scan or full body X-ray scan data of the person. This work can be done using a non-rigid registration method.
- Morphing: In DACAA program, a method was developed for morphing a parametric finite element model to a surface (shape) model. The process begins with statistical models of human geometry (skeleton and external body surface) that describe morphological variations within the population as functions of human parameters (age, sex, stature, and/or body mass index). Mesh morphing methods are used to rapidly morph a baseline human model into other geometries while maintaining high geometry accuracy and good mesh quality. Given a target age, sex, stature, and body mass index, the statistical human geometry models developed previously predict thousands of points that define the body posture, the size and shape of the external body surface, and ribcage and lower extremity bone geometries. The skeleton and external body shape geometries are integrated together based on the landmarks and joint locations shared in both models. Once the target geometries are developed, the baseline model is morphed to match the target geometries using a technique based on radial basis functions, as shown in Figure 4.
- Scaling: To create an individualized musculoskeletal model from its template, we will use the full body finite element model of this person to determine his joint centers and calculate linkage lengths and segment inertial properties. These parameters will be then used in OpenSim to calculate scaling factors for scaling the template model to the individual model.

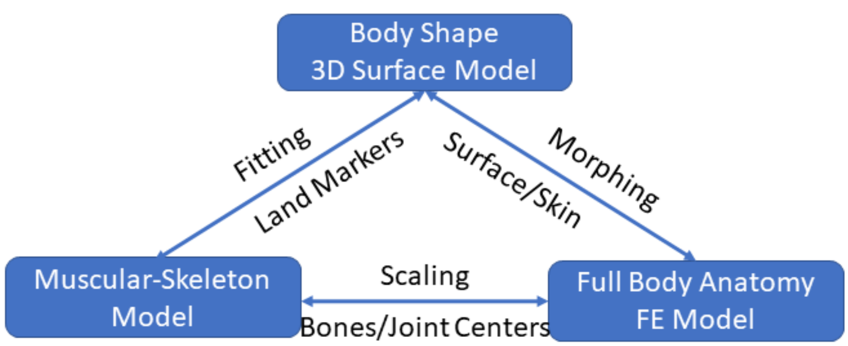



Figure 3. Unification and individualization of human models.

The individualized models created from the templates provide an acceptable approximation to the ground truth, having a level of details and medical fidelity that meet the requirements of many applications. This approach is the primary method that we will use to create HDTs. Alternatively, to attain a higher level of details and fidelity, full body finite element model can be created from MRI or X-ray data directly, which requires specialized efforts that may exceed practical safety and financial limits. The MRI scans of the whole body are extremely rare due to motion artifacts from internal organs. MRI of large portions of anatomy are extremely expensive. The X-ray CT scans are rarely performed for ethical reasons unless there is a critical health risk that warrants the very high X-ray dose received. A full body musculoskeletal model can be created from motion capture data by registering virtual markers on the template model in OpenSim with the markers placed on the body.

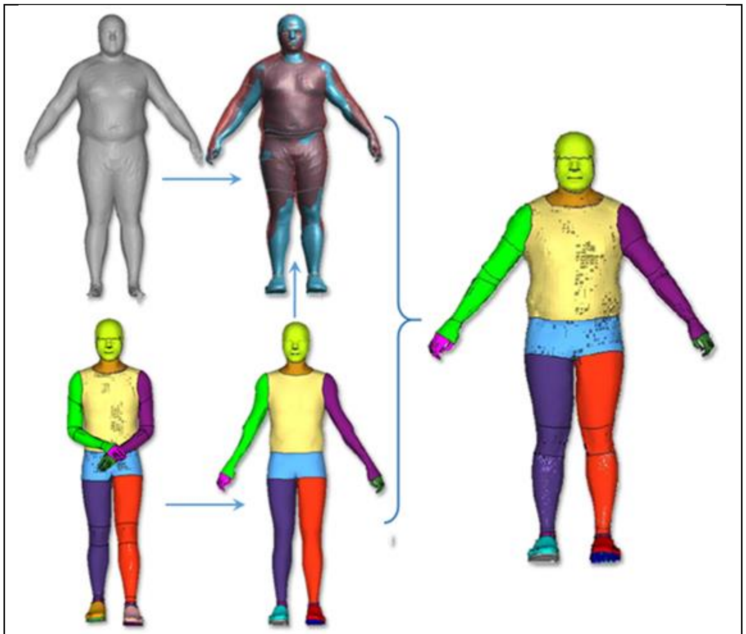


Figure 4. Morphing an FE model to a target body surface.

### 3.4 Data Containers with Data Driven Models

Data containers with data driven models are used for HDT to describe the human characteristics of physical components not fully parameterized or modeled. A conceptual design of HDT data containers is shown in Figure 5. Data analytics and machine learning can be applied to these data to create data driven models, which range from basic linear regression models to sophisticated DNN models (Brunton and Kutz, 2019).

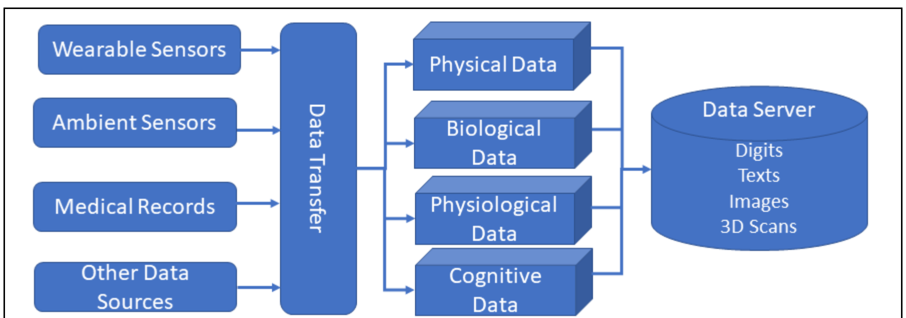



Figure 5. Data Containers for HDT.

## 4. APPLICATIONS

HDT has wide applications in human-centered products, services, and performance, such as digital health or telehealth, human-machine interface, fit and accommodation, physical therapy, and physical training. Two funded projects are briefly described as follows.

**4.1 Patient Digital Twin for Scoliosis Physiotherapy**

This is a small business innovative research (SBIR) Phase I sponsored by National Science Foundation. In this project, the patient digital twin as a digital or virtual copy of an individual patient is created from body scan and X-ray images. It allows the diagnosis of scoliosis and the assessment of spine deformity to be performed in 3D space, thus improving the completeness of assessment and the design of PSSEs. By graphically displaying muscles involved in a PSSE and the effects of muscle activation and stretching, a physiotherapist can clearly explain the cause-effect of a specific PSSE on the spine deformity. The prescribed PSSEs are represented by 3D games by animating the patient digital twin with motion captured during clinic practice. Then, with a home-based performance capture device, the actual poses and motion of a patient during home exercise can be monitored, evaluated, and instructed to adjust with 3D games as reference.

| (a) Body scan | (b) X-rays | (c) Skeletal model | (d) PDT |
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Figure 6. Human digital twin for a scoliosis patient.

Scoliosis PDT, as shown in Figure 6, is created through individualization process which includes multiple steps as follows.

1) Shape model creation. In clinic or at home, the patient's body shape can be captured by Kinect and then the body shape model can be readily created from depth images. After a shape is derived from 3D point clouds, it will be parameterized by projecting the model in an eigen space composed by principal components of human body shape.
2) MS model creation. Usually, a Scoliosis patient will not do a body CT scan, instead, X-ray images are often taken. Therefore, in the current stage we will focus on utilizing X-ray images to create an instance MS model from its template via the following procedures.
   - Scaling: we will first scale the musculoskeletal model based on the subject's height and weight. Then, the body segment lengths will be adjusted according to the skeleton model provided by Kinect. This will be done using OpenSim which runs on the central server.
   - Skeleton morphing: we have developed a method for skeleton morphing, which includes four steps: (a) Registration: to register x-Ray images (back and side views) which are usually taken for a patient to the body shape model in the coronal plane and sagittal plane, respectively; (b) Spine reconstruction: to reconstruct spine column from c1 to L5 in 3D space based on the registered and calibrated X-ray images; (c) Match: to match each vertebrate from MS template model with the counter one from the reconstructed patient spine by adjusting vertebrate disk position and orientation; and (d) Morphing: to morph other bone structure of the template MS model accordingly assuming that the connection between a bone (e.g., rib) and its attached vertebrate is rigidly.
   - Muscle morphing: The muscle groups of the MS template model will be adjusted in length, orientation, and attachment accordingly based on the skeleton structure of the patient. As such, the

MS model for a patient can be quickly derived from the template MS model to match his/her actual height, weight, and spine curvature. This model provides a sound approximate modeling of the muscular skeleton and can be used to define/demonstrate a pose, to replicate a motion, and to compute scoliosis curves (Cobb angles), thoracic kyphosis (T4-T12 Cobb angle) and lumbar lordosis (L1-L4 Cobb angle) for an individual patient.

3) Integration. The shape model and the MS model will be integrated to become a full body model by associating the body surface vertices with its underlying bone structure. As such, realistic body deformation can be attained when the entire body is articulated. The integrated model constitutes the main part of patient digital twin. In addition, we use data containers to hold other physical and physiological data, pose data, motion capture data, and other medical information.

**4.2 Pilot Digital Twin (PDT)**

This is a SBIR Phase I sponsored by the United States Air Force. As shown in Figure 7, Pilot Digital Twin, as a virtual copy or digital representation of an individual pilot, is composed by physics-based human models, data-driven models, and data containers linked to wearable sensors, cockpit environments, and other data source. It provides integrated, holistic, and dynamic representation of physical/ physiological attributes of an individual pilot and tracks a pilot's physical and physiological performance and health status. It can be used for (a) Personalized design and fitting of pilot gears and equipment; (b) Adaptive cockpit accommodation; (c) Personalized physical fitness training and mission performance training; (d) Acute and chronic injury mitigation; and (e) Physiological status monitoring and prediction.

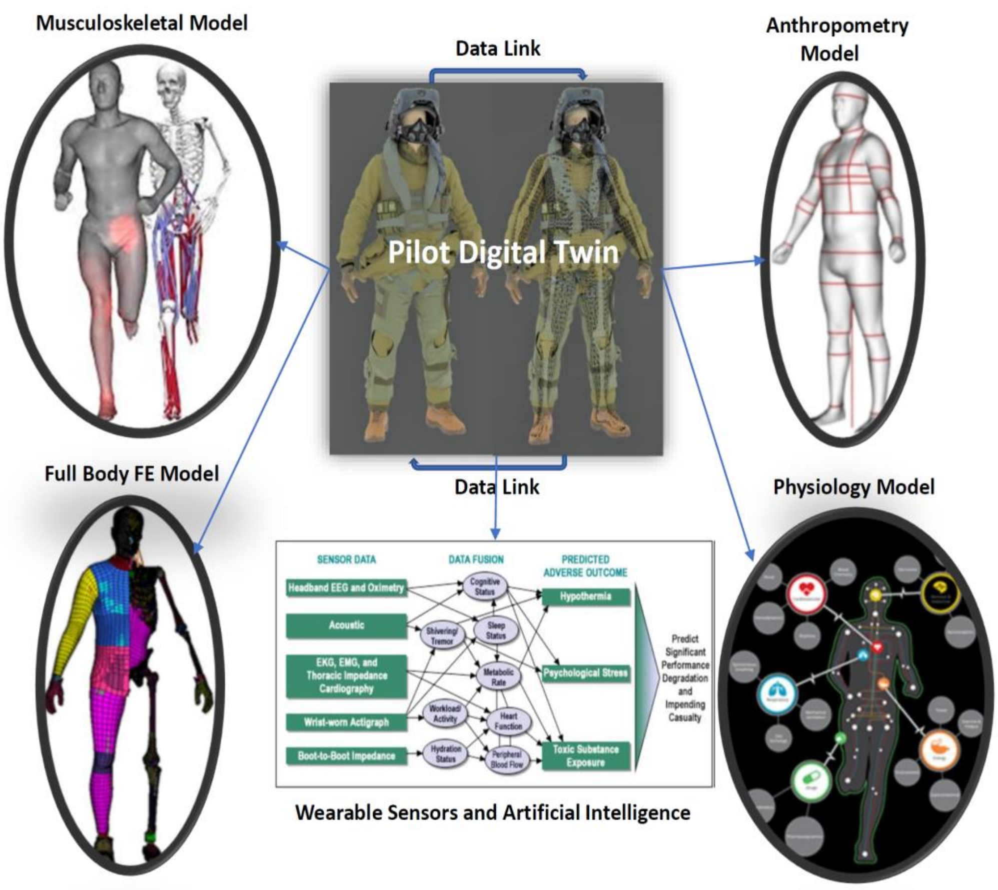


Figure 7. Pilot Digital Twin (PDT)

## 5. DISCUSSION

Digital twins have become an enabling technology implemented by industry in recent years (Grieves 2021). We introduced the development of the HDT technology that could be used for various applications. The human body is a complicated biological system. Any digital representation or virtual copy of human body is an approximate representation with the limited level of details and bio-fidelity. The same is true for the HDT presented in this paper. For the HDT introduced in this paper, we use physics-based digital human models (unified and individualized) and data containers with data analytics. Based on the data collected by a HDT, various data-driven models can be derived, ranging from the simplest regression models to the most advanced deep neural network models. While many human characteristics can be effectively and rigorously represented by physics-based digital models (e.g., anthropometric and biomechanical features), others (e.g., cognitive and behavior attributes) can be more easily described by data-driven models. Moreover, human characteristics can be described by a hybrid model that integrates a physics-based model with a data-driven model (Brunton and Kutz, 2019).

A data link can be established between a HDT (HDT) and its biological counterpart to synchronize their dynamic states in real-time. This clearly differentiates a HDT from a traditional human model or an individualized avatar which is manipulated by user commands. The future states predicted by use of the digital twin's multisystem data can be fed back to human via the data link. If the digital twin is considered as a body, data stream is the 'blood' of the body. In practice, the physics-based models of the HDT need to be updated periodically according to substantial body changes induced by injury, physical training, or other causes. The data-driven models of the HDT can be updated more frequently, or in real-time, based on the data stream from wearable sensors/other sources. If a HDT were to accompany its biological twin for a significantly lengthy period, it would need to reflect changes during growing and aging processes.

The development of the HDT technology will be a progressive process from its current rudimentary form to a full scale, accurately-modeled digital twin in the future, incorporating state-of-the-art technologies that improve its level of details and bio-fidelity. Regarding the HDT described in this paper, extensive efforts are still required to complete development and to fulfill its designated functions. From general HDTs which are for average people, digital twins can be created for a specific group of people with common environments, needs, requirements, or purposes, such as patients (e.g., scoliosis patients or those with chronic back pains), Warfighters (e.g., pilots), athletes (e.g., football players), astronauts, fire fighters, first responders, etc.

As the HDT contains personal data, the information security and privacy protection become important issues. During HDT design and development, various measures can be adopted for information security and privacy protection. During HDT utilization, strict procedures need to be implemented for the data access. Policies may need to be established at high levels for HDT management.

## 6. CONCLUSIONS

The concept of human digital twin along with an approach to construction was presented. By using individualized, unified physics-based models, HDT can effectively describe human physical and physiological characteristics. By using data containers linked to data streams, HDT can reveal personal status and performance in a timely fashion. By using data driven models, HDT can represent human cognitive, behavioral, and other performances. Integrated with physics solvers, HDT can be used to analyze and predict human physical and physiological status under force, acceleration, and other extreme conditions. Integrated with wearable sensors and ambient sensors, HDT can be used to enhance and expand human performance monitoring and assessment. There are various potential uses of HDT in the integrated digital environments or metaverse. HDTs can work with advanced digital technologies including big data, data analytics, deep learning, and artificial intelligence to protect, enable, and empower individual human.

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