Proceedings of the Canadian Society for Mechanical Engineering International Congress
32nd Annual Conference of the Computational Fluid Dynamics Society of Canada
Canadian Society of Rheology Symposium
CSME-CFDSC-CSR 2025
May 25–28, 2025, Montréal, Québec, Canada

Advancing Human Digital Twin: A Mini Review of Human Modelling

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Abstract—The human digital twin (HDT) represents a comprehensive digital counterpart of an individual, integrating biophysical, cognitive, psychological, and social attributes. The concept of HDT comes from the conventional digital twin used in industrial engineering. Its application extends into personalized healthcare, smart manufacturing, and human-centered systems. This paper reviews the evolution of human modelling, from early physical representations to modern digital simulations, leading to the development of HDT. A key focus is unified HDT information modelling, consolidating diverse human attributes into an integrated information model. The paper categorizes essential HDT components, including physical, mental, psychological, ability, activity, and social-connection models. Additionally, This paper highlights challenges such as data and software standardization, privacy concerns, technical limitations, and the complexity of modelling dynamic human characteristics. Addressing these challenges will be crucial for advancing HDT applications in industry and healthcare. Future research directions include exploring data collection and simulation methods to empower the HDT functions in real-world applications.

Keywords: Human Digital Twin, Digital Human Modelling, Digital Twin, Information Model

I. INTRODUCTION

The human digital twin (HDT) is a precise digital representation of an individual, incorporating biophysical, biochemical, mental, psychological, and social attributes [1]. The concept of HDT originates from the conventional digital twin used in industrial engineering for physical entities like machines, tools, and devices. In this context, a digital twin serves as a comprehensive, multi-physics, and multi-scale simulation of a system, utilizing advanced physical models, real-time sensor data, historical records, and other inputs to replicate the behaviour and lifecycle of its physical counterpart [2]. A global marketing analysis forecasts that the digital twin market will expand from USD 9.9 billion in 2023 to USD 125.1 billion by 2032, reflecting a compound annual growth rate (CAGR) of 33.3% [3]. Major industries driving this growth include manufacturing, healthcare, and automotive, where human interaction plays a crucial role. Meanwhile, research has indicated that the upcoming Industry 5.0 will be human-centric, fostering a manufacturing environment that prioritizes worker welfare and promotes efficient collaboration between humans and machines [4]. Given that HDT specializes in simulating and predicting human-related processes, advancements in HDT technology are expected to strengthen human participation and improve well-being within these industrial sectors.

Within the HDT framework, digital human modelling plays a key role by offering comprehensive insights into the human body. Unlike traditional digital human geometric modelling, which primarily captures physiological data such as body dimensions and spatial relationships between body parts, HDT-based human modelling extends beyond this by incorporating psychological and mental attributes, including attention, intention, and emotions. Current review studies have explored the application of HDT across various domains—for example, Hu et al. [5] examine its role in autonomous driving and intelligent vehicles, while Okegbile et al. [6] and Barricelli et al. [7] focus on its use in personalized fitness and healthcare. Wang et al. [8], Kim et al. [9], and Duffy [10] discuss its impact on worker safety, ergonomics risks, and enhancing human-machine collaboration in smart manufacturing. Additionally, Hlis et al. [11] investigate its application in sports practices. However, these studies primarily emphasize validating the advantages and connections between HDT and various application domains (e.g., HDT and vehicles in autonomous driving, HDT and machinery in smart manufacturing) rather than centering on HDT itself. In the meantime, although some studies have explored the framework of the HDT—for example, Wei [12] validates the feasibility of constructing the HDT and highlights its role in enabling full lifecycle health management, while Miller and Spatz [1] examine the development of a unified HDT information model—these works primarily adopt a holistic scope on HDT rather than emphasizing its human modelling aspect. To address this gap, this paper mainly reviews HDT modelling by exploring the evolution of human modelling, the current state of unified HDT information modelling, and the challenges associated with HDT modelling.

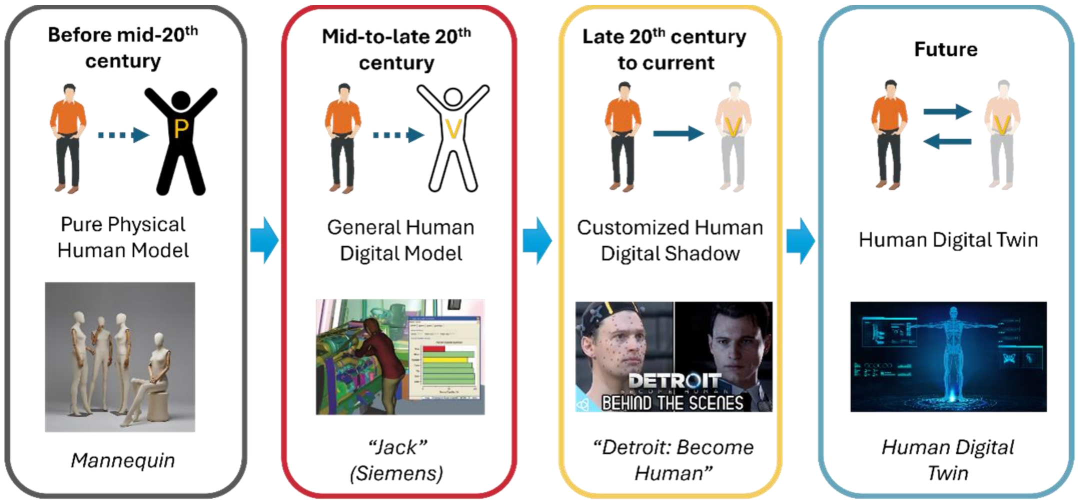


Fig. 1 Development of human modelling

The following contents are structured as follows: Section II explores the development of human modelling from ancient to modern times. Section III examines the current unified HDT information modelling, discussing the types of human information from current literature to be included in the HDT. Section IV addresses the challenges in HDT modelling. Finally, Section V summarizes this work and discusses future works.

II. Evolution of Human Modelling Technology

The development of human modelling is strongly influenced by breakthroughs in material science, digital hardware, data-processing methods, and computational power. As shown in Fig. 1, such a development can be divided into four key stages: purely physical human models, general virtual human models, customized virtual human models enhanced with sensor data, and customized virtual human models featuring bi-directional data exchange.

A. Pure Physical Human Models

Before the mid-20th century, physical human models were created to represent the external appearance (e.g., Greek sculptures, Barbie dolls) or internal structure (e.g., skeletons, organ models) of humans based on empirical and anatomical knowledge [13]. These models served various purposes, including art, product demonstration (e.g., mannequins), and medical training (e.g., first-aid dummies). The model customization depends on the purpose of use—for example, a personalized sculpture needs to resemble each individual, while a first-aid dummy only requires a generic human form. Although most physical models in this stage are static, some can physically simulate human biological processes. An example is shown in Fig. 2(a), which is the human meridian model from the Chinese Song Dynasty (960–1279 BC). Made of hollow brass, this model was used to train acupuncture practitioners by leaking water from meridian holes when pierced correctly [14]. Modern human physical models, enhanced by the development of electric sensors and computer techniques, enable real-time simulation. For example, as shown in Fig. 2(b), crash test dummies equipped with kinematic sensors analyze the physical impact on drivers and passengers during vehicle collision tests.

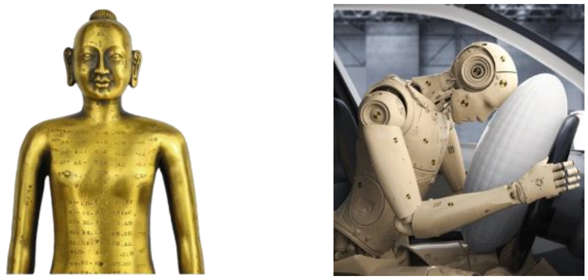
B. General Human Digital Models

With the advancement of computer graphics and data processing in the mid-to-late 20th century, virtual human models could be created digitally. This stage introduced digital human modelling (DHM), a tool allowing the simulation of a range of human sizes and shapes to evaluate factors such as fit, reach, and vision in computer-aided design (CAD) software [15]. DHM systems like SAMMIE, shown in Fig. 3, were used to assist in tasks like estimating passenger capacity in trams [16] and evaluating truck blind spots [17].

Due to cost concerns and the intended purpose, the DHM in this stage was not tailored to individuals. Instead, statistical data from earlier studies, like Barter et al. [18] on joint movement, Wald [19] on vision, and Sheldon [20] on body shape, were used to build the human digital model. This limited personalized customization makes the DHM insufficient to replace physical prototypes or real-life fitting trials completely [15].

C. Customized Human Digital Shadow

Since the late 20th century, wearable sensors have been incorporated into digital human modelling, making it possible to create more personalized virtual human models. This stage is called the "digital shadow" phase, where personal data is transferred from the physical human body into a virtual model. The first wearable sensors, developed for space missions, tracked astronauts' health parameters like heartbeat, breathing, and body temperature [21]. Over time, wearable devices became smaller, lighter, and more comfortable, with products like the Apple Watch integrating multiple sensors to monitor health and motion. Along with these advancements in wearable sensors, machine vision and computer graphic techniques enabled the creation of personalized models that could track human haptics and motion [22]. Combining these technologies allows a more accurate digital representation of a person, which can even animate their movements. Furthermore, these personalized models enable researchers to simulate and predict human behaviours based on individualized data, such as movements or actions in a built environment.



(a) (b)

Fig. 2 (a) The brass human meridian model. Meridian poles are filled with water and wax-sealed during acupuncture training. (b) The human dummy with motion sensors for vehicle crash test.

However, despite the advances, current simulations still have limitations. For example, they often rely on professionals to analyze data manually, which can be inefficient due to the complexity of human behaviours. In the meantime, while some models include biological characteristics like heart rate or motion [23], they do not yet integrate comprehensive digital representations of the human body's geometry.

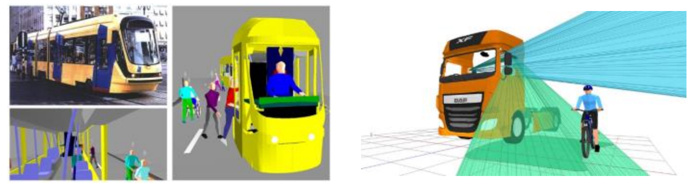
D. Human Digital Twin

The future of human modelling focuses on cost-efficient, automated, and low-effort methods to create comprehensive digital models of individuals. These digital models will integrate diverse human-related data, including geometric, biophysical, mental, and social information. Simulations will use this data to replicate human activities, predict outcomes, and provide feedback, addressing internal variations (e.g., heart rate) and external interactions (e.g., driving). The ultimate goal is to develop human digital twins (HDT), the virtual replica that enables real-time simulations and decision-making in various human-related application fields, such as healthcare, sports and fitness, and human-centred manufacturing, with seamless data exchange between humans' real and virtual counterparts.

III. Existing HDT Information Models

The HDT information modelling aims to build HDT by including all perspectives of an individual's information and simulating correlated human-related activities. Several previous studies have investigated what types of information need to be included within a unified HDT information model.

According to Miller and Spatz [1], a unified HDT information model should include at least one of the following attributes: physical details (e.g., age, gender, height, weight), physiological data (e.g., heart rate, blood pressure, fatigue, alertness), perceptual abilities (e.g., sensitivity to light, sound, colour), cognitive skills (e.g., knowledge, aptitude), personality traits (e.g., trust tendency, attributes), emotional states (e.g., anxiety, depression), ethical values (e.g., beliefs, life values), and behavioural patterns (e.g., interactions with the environment or others). In another study, Toshima et al. [24] explore the concept of Human Digital Twin Computing (DTC), a technology designed to digitally replicate not only a person's external physical traits but also their inner attributes. The study classifies virtual human entities into seven distinct domains: personality (e.g., personal values, behavioural tendencies),



(a) (b)

Fig. 3 (a) The tram design (b) The truck blind spot evaluation [8].

abilities (e.g., perception, physical skills, knowledge, language proficiency), social (e.g., address, occupation, interpersonal relationships), physiological (e.g., blood pressure, heart rate), psychological (e.g., emotions, mood, attitude), activity (e.g., physical movements and behaviours), and environmental context (e.g., temperature, humidity). Unlike Miller and Spatz [1] and Toshima et al. [24], which focus on listing various human attributes for building the HDT, Lin et al. [25] provide a more comprehensive approach by categorizing different human properties into broader categories. This work highlights that a general-purpose HDT model should encompass five key information domains: human external data (e.g., age, gender, height, weight), physiological data (e.g., heart rate, blood pressure, body temperature), behavioural data (e.g., walking, running, jumping), social interaction data (e.g., online activities, personal relationships), and environmental data (e.g., temperature, humidity). He et al. [26] gives a more general definition by addressing that the HDT only needs three types of information model: the health model, the cognitive model and the biomechanical model. Specifically, the health model encompasses information about an individual's mental and physical well-being. The cognitive model covers details related to an individual's perception, awareness, and memory. Meanwhile, the biomechanical model includes data on an individual's anthropometry, musculoskeletal system, and information on kinematics and kinetics.

In addition to discussing the unified HDT model, some studies focus on specific topics involving humans, like smart manufacturing and autonomous driving. They explore what properties or functions need to be included in the HDT to suit these fields. In smart manufacturing, Wang et al. [8] provides a comprehensive review of the HDT development in Industry 5.0, which highly emphasizes human-centred manufacturing. The review details various information models within the HDT system, including physical, psychological, cognitive, and interaction models. The physical model captures human geometric, motion, and ergonomic data for motion detection, prediction, and optimization applications. The psychological model leverages emotional and mental workload data to monitor and predict emotional states and assess mental workload. The cognitive model analyzes intentions and decision-making to anticipate human actions. Lastly, the interaction model addresses trust and management mechanisms to optimize task allocation, factory design, and human-robot collaboration in smart manufacturing environments. In autonomous driving, Hu et al. [5] introduce the concept of a driver digital twin (DDT), a virtual representation of human drivers designed to improve intelligent interaction between humans and vehicles. Their research emphasizes the need to gather comprehensive data on a

TABLE I Categorized HDT Information Models in Reviewed Literatures

Categorized HDT Information Models	HDT Information Models in Literatures					
	Miller and Spatz [17]	***Toshima et al. [18]***	***Lin et al. [19]***	***He et al. [20]***	***Wang et al. [21]***	***Hu et al. [22]***
Physical Model	• physical details • physiological data	• physiological context	• human external data • physiological data	• health model • biomechanical model (partially)	• physical model	• physical condition
Mental Model	• emotional states • ethical values					• emotional states • intention (partially) • attention (partially)
Psychological Model	• personality traits • perceptual abilities • cognitive skills	• personality • psychological context		• cognitive model	• psychological model • cognitive model	• intention (partially) • attention (partially)
Ability Model		• ability			• interaction model	
Exercise/Activity Model	• behavioral patterns	• activity	• behavioral data	• biomechanical model (partially)		• behavioral patterns
Social-connection Model		• social context	• social interaction data		• interaction model	

driver's emotional state, behavioural patterns, physical condition, intentions, and attentional focus to construct the DDT. By leveraging this data, the DDT enables diverse assessments of driver behaviour, including detecting distractions, estimating attentional focus, predicting driving intentions, identifying drowsiness, tracking emotional states, evaluating trust in vehicle automation, and recognizing individualized driving behaviours for personalization. Using the assessment results from the DDT, the autonomous vehicle, as a cyber-physical system, can enhance its advanced driver assistance systems (e.g., adaptive cruise control, forward collision warning, lane-keeping and lane-changing, and human-centred shared control), personalize the human-vehicle interface, and improve its autonomous driving capabilities.

In summary, while many studies on unified HDT models include diverse information components, several terms overlap conceptually. For example, terms like "physical information," "biomechanical model," and "physical model" describe human physical properties, such as external body geometry (e.g., height, weight) and internal biological traits (e.g., blood pressure, heart rate). Based on the reviewed works, a unified HDT comprises components like a physical model, mental model (perception and cognition), psychological model (emotion and feelings), ability model, exercise/activity model, and social connection model. TABLE I showcases how human information components from the reviewed literature are categorized. Additionally, it is worth mentioning that although some previous works include an environmental model, these primarily describe environmental properties rather than how they affect human individuals. Such an environmental aspect lies outside human autonomy and should not be considered part of the HDT.

IV. Challenges in HDT Modelling

The challenges of human modelling in HDT arise from humans' high complexity and dynamic nature, technical limitations, lack of standardization, data transmission and security issues, and concerns about privacy and bias.

A. *High Complexity and Dynamics*

Unlike building virtual digital twin entities for manufacturing machines and equipment, where their geometric structures and functions are intentionally designed and defined during production, humans are highly complex physical systems. They not only encompass multiple physical properties but also integrate perceptive, cognitive, and social-related information. Therefore, the virtual entity of an HDT needs to comprehend not only the human geometric profile, behaviour patterns, and physiological state but also the individual's underlying intentions and preferences [27]. In addition to their complex structure, humans exist in highly dynamic environments, causing their characteristics and conditions to change rapidly [28]. Because of the complexity and dynamics of the human body, HDT modelling faces challenges in achieving sufficient fidelity and flexibility to capture human-related data across multiple scopes and at a rapid pace.

B. *Technical Limitation*

It is challenging to permanently measure all dimensions of human data due to the lack of suitable sensors that can be attached to or integrated with the human body for extended periods. While some wearable devices can collect users' data during use without significantly interfering with daily life and work, their measurements are confined to essential physical attributes like heart rate, blood pressure, and body temperature. Research using wearable sensors to assess complex human characteristics, such as cognitive function, attention, and intention, remains in its early stages [29]. Beyond lacking proper sensors, human sensitivities toward intrusive technologies are another concern. For example, some HDT application research focuses on lumbar spine analysis and requires humans to wear virtual reality (VR) headsets embedded with inertial motion unit (IMU) sensors to capture motion profiles [30]. However, monitoring human motion with such equipment may not be feasible in real working scenarios, as wearing the equipment can interfere with proper action performance, and the sensors' functionality may be affected by the complex electromagnetic environment in the workspace. Some studies address the challenges of wearable measurement devices by adopting non-contact approaches, such as depth cameras [31] or deep learning-based computer vision frameworks [32], to capture human haptics and motions. However, the accuracy of these methods still requires validation.

C. Standardization

The standardization challenges in HDT modelling are highlighted from two perspectives: determining the types of human information to collect and selecting the platform or software for storing and processing the collected data. Section III presents previous studies that propose the types of human-related data necessary for constructing the HDT model. While six categories of information models—physical, mental, psychological, ability, exercise/activity, and social connection—are summarized at the end of the section, their necessity and distinct differences require validation through specific HDT-related simulations and case studies. Regarding the modelling platform and software, HDT requires a system capable of generating an executable digital human model based on individual profiles. Currently, no specific software or software type has been standardized for HDT modelling. However, several potential options could support this process, including human-centred design and simulation software (e.g., Siemens NX Modeling, RAMMIS), 3D computer graphics software (e.g., Blender, MakeHuman, Maya), computer-aided design (CAD) software (e.g., SolidWorks, Rhinoceros 3D), and game engines (e.g., Unity, Unreal Engine).

D. Data Transmission and Security

HDT modelling creates large amounts of high-resolution human-related data, such as biomedical signals, motion tracking, and environmental interactions. Transferring this data for real-time simulation requires a robust network framework to ensure low-latency and high-reliable communication. In the meantime, a large amount of data may be exposed to cyber risks, like unauthorized access, data breaches, and tampering. Protecting privacy and keeping data safe requires methods like end-to-end encryption, using blockchain for secure data records, and applying strong access controls.

E. Privacy and Bias

HDT modelling needs to prioritize data privacy due to the sensitivity of human-specific information. This requires the modelling process to imply advanced security measures, adhere to regulatory standards, and adopt a user-friendly and human-centred development approach to foster trust and address data-ownership issues for human individuals. In the meantime, to lower the data bias, HDT modelling needs to be universally accessible, ensuring inclusivity across nations and social demographics. Considering how distinct social groups engage with HDTs and ensuring equitable representation in the data can mitigate the risk of reinforcing social inequalities and biases [28].

V. Conclusion

This study provides a comprehensive review of HDT modelling, emphasizing its evolution, the unified HDT information framework, and the challenges that need to be addressed for its application. Tracing the historical development of human modelling—from purely physical representations to modern digital twins—highlights the increasing integration of biophysical, cognitive, and social attributes in HDT systems. This research consolidates existing literature on HDT information modelling, categorizing key human attributes necessary for a unified HDT system, including physical, mental, psychological, ability, activity, and social-connection models.

Future research based on this paper could explore methods for capturing data to integrate into the unified HDT information model and how this model can facilitate human-related simulations across various applications.

Acknowledgements

Funding: This research received financial support from the Social Sciences and Humanities Research Council (SSHRC) through the New Frontier Research Fund - Exploration Grant (NFRFE-2022-00081).

Conflict of interest: The authors declare no competing interests.

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