A template for digital human representation in digital twin simulations of social human-robot interaction

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***Abstract*—The virtual validation of a robot's social capability using digital twins requires assessing the perceived quality of human-machine interaction, reflected through various observable human parameters that influence the comfort experienced during the interaction. Due to this reason, the detailed digital representation of humans in such simulations is as essential as it is difficult to achieve. This paper introduces a template for digital human representation in a digital twin intended for simulation scenarios of social human-robot interaction. Parameters and properties are grouped into categories for physical behavior, physiological condition (including health), social-cognitive behavior, visualization, and sensory capabilities describing a simplified digital representation of a real-world person. The proposed model parameters are chosen based on a literature review of published work regarding digital twin solutions for applications in social robotics with a focus on human digital representation.**

***Index Terms*—Digital twins, Social robots, Human-robot interaction, Human-machine systems, System implementation**

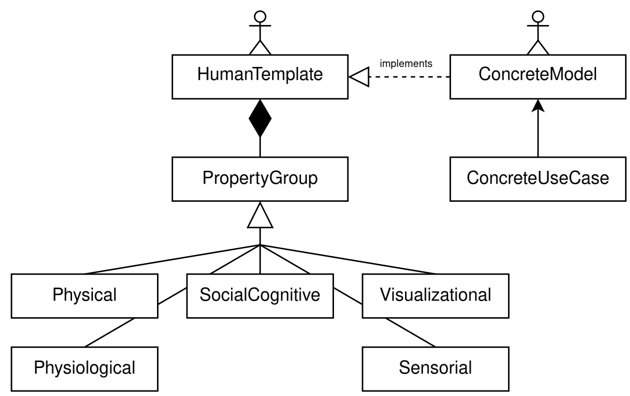

Fig. 1. Template of a digital human representation with property groups. *(Courtesy of CDM)*

I. Introduction

During Human-Robot Interaction (HRI), a robot's social capability is essential for highly perceived comfort, which depends on various social-situational parameters like movement, noise, emotions, or stress [1]. However, the virtual validation of social skills of a robot's deployed behavior model via simulation also requires the human side, whose digitization is complex and challenging. Most scientific works on HRI simulation using the modern Digital Twin (DT) approach only focus on a subset of model parameters and properties relevant to the posed problem statement. These could be a more detailed view of human emotion, medical aspects, or workplace ergonomics. Such can all have equally relevant impacts on an interaction's perceived comfort, which naturally indicates a robot's general social capability.

A. Motivation

Observed and quantified human parameters can aid in inferring the HRI's perceived comfort used to measure robotic social skills. Therefore, this paper aims to identify and categorize common human property groups discovered in recent work. The result is a template version of a digital human representation for said simulation scenarios, acting as a common foundation upon which new use cases can be built. Different implementations serving specific problem statements would implement aspects of the proposed template in more detail, visualized in Figure 1. Namely, this paper intends to answer the following questions:

What are commonly applicable sub-models in human representation? This question regards relevant categories of digitized human models in DT simulations.

What are relevant properties and parameters in human digitization? Each category contains a set with human properties/parameters representing relevant aspects in DT-based simulations of HRI.

Which properties are considered in modern research? The presented template stems from a literature review for discovering human model parameters and properties.

B. Outline

After this introductory Section I, the following Section II gives an overview of the relevant research about the Human Digital Twin (HDT) and DT-based simulation of social robots. Section III presents the proposed digital human template. Section IV gives an overview of discovered human model parameters from recent research work regarding DT-simulations of HRI. Finally, the paper concludes with Section V and VI with an outlook for future work.

II. Related Work

A. The digital twin

During recent years, the DT has gained popularity in the current trend of Industry 4.0 [2], [3] with its application possibilities outside of digital manufacturing also ranging into other fields like healthcare [4], [5] or robotics simulations [6]–[8]. While it has become a general method to represent real-world assets and processes digitally in real-time [9], its definition is partly ambiguous [10]. Aspects like synchronization between the digital and physical side can be open for discussion: The authors of [11] see the DT characteristic satisfied if and only if the digital representation and its physical counterpart are fully synchronized. Though, indeed, the exchange of data and operational information between the real and digital side is a core aspect of the DT concept [12], one can challenge the synchronization constraint for use cases digitizing a physical asset via a DT solution but still in a prototyping phase and therefore either partly theoretical or operating on test parameters [13]. In such cases, only a simulation as close as possible to the designed physical prototype would exist with the advantage of test data generation before any investment into the physical assembly, which can be time- and cost-intensive, especially for robotics scenarios. Other definitions like the five-dimension DT as presented in [12] mainly highlight the bidirectional communication and data exchange between physical and digital assets supported by case-specific data management. Various other definitions exist [10].

This paper regards the digital twin as a digital representation to simulate and prototype a physical or conceptual system, like a robot in a HRI scenario. The DT is not required to map a physical system's state in real time and synchronously. It merely digitally represents its physical or theoretical counterpart. Through bidirectional data exchange, the physical state maps onto a defined data scheme like the one presented in this paper specifically for human models. If data exchange occurs in real-time during run-time, the DT is synchronized.

B. Human digitization via human digital twins

It is generally impossible to entirely omit the human worker from the equation in a digital manufacturing setting [14]. Furthermore, other applications like Collaborative Robot (Cobot) simulations as in [15] require some form of human modeling to be expressive. Therefore, a logical next step to the general DT approach is the digitization of humans aimed at representing persons like industrial workers or patients in a digital environment. A system with this goal is called a HDT [16]–[18]. Like the general DT, its definition is ambiguous. Its appearance can also vary in several ways depending on the field of application. To name an example, the HDT shows potential in the Smart Healthcare sector [4] creating a digital replica of given patient data as presented in [5]. This approach uses medical data to simulate the human system or parts of it, like individual organs, and create a diagnosis through the application of techniques from computer vision. In these scenarios, the HDT would be close to a digital shadow [19], which is the digitally stored status data also present in each DT. The HDT also plays a role in applications outside the medical sector, like human-cyber-physical systems. The model presented in [20] fuses sensory data about a human's physiological status parameters like body temperature and physical status parameters like human motion to create a controllable digital avatar. Regarding human digitization, the preliminary model presented in [21] aims to describe the necessary properties with a strong focus on the relations between them, rendering it difficult as an implementation basis, also lacking proper categorization of said properties.

This paper defines the HDT as a DT containing a subset of the following proposed parameter and property groups representing a digitized and abstracted version of a person.

C. Simulation of social robots

Social robots can emulate social competence when interacting with humans. They find applications, among others, in healthcare [22]. Social competence is evaluable using diagnostics tools for human-robot collaborative tasks as presented in [23], measuring the quality of the interaction by considering human stress responses. The simulation of social robots brings the advantage of having a virtual prototype before assembling a physical counterpart.

In [24], a socially aware robot drone for home care of dependent people utilizes visualized human models in a simulated environment. Using facial detection and emotion recognition within the virtualization allows the social robot to generate knowledge of a person's emotional state and react accordingly. Other systems implement social behavior through movement intention prediction of human workers achieved through probabilistic models [25], navigational solvers [26] or learning of movement primitives [27]. The simulated social robot adjusts its movement trajectory to prevent collisions, maintaining a minimum safe distance to the persons in a workspace. In [15], a simulation of collaborative assembly between humans and robots places both in a shared virtual environment. The system aims to support the worker by identifying human actions in a sequential collaborative assembly task to react accordingly.

This paper discovers and categorizes common properties and parameters of the human models used in recent work on simulations of social robots.

III. A template for human digitization

To account for the large number of application scenarios revolving around HRI, a digital human template for human digitization within a HDT is proposed consisting of relevant model parameters frequently expressed in recent research. The model is visualized in Figure 2 and explained in this section per property group. The proposed categories originate from the four capability classes of the Operator 4.0 model as defined in [28], which are physical, cognitive, sensorial, and interaction capabilities. The physical aspect splits into a human's physical behavior and a physiological condition, which includes health. Furthermore, visualization properties replace interaction because the inclusion of explicit methods of interaction would break simplicity. Additionally, interaction with an operator in a virtual 3D environment requires visualization.

A. Definitions of property groups

As visualized in Figure 2, the template consists of a selection of property groups implementing an aspect of the model. A specific use case can implement a selection of properties in a structured manner. The indicated data types are suggestions depending on the digitized property and provide further context. For social-cognitive values like stress, a percentage indicator represented through the float data type acts as a simplification. More complex or inferred variables do not feature data types in the template.

1) Physicals: This group contains the physical and mechanical properties relevant to physics-based simulations of humans. Some of these aspects can overlap with the physiological category, like regarding body weight from a medical and human mass from a physical standpoint. The physical property group contains the human pose, featured in several simulation applications in Section IV. Basic tracking is simple as long as no occlusions occur. The template also consists of the digitized human's physical shape represented by a 3D model. Together with the human pose, this data is usable in kinematic calculations like inertia, which requires a body's center of mass. Additionally, the template stores collision information as a bounding volume relevant for indicating the minimum safe distance to the actor in a HRI-workspace.

2) Physiologicals: This group contains the medical and physiological information on the digitized human body. It splits into two main parts: The body shape of the described person containing properties like age, gender, height, weight, etc., and strictly time-dependent data in the form of a physiological state, which is trackable during the HRI scenario. The body shape also depends on the physical body shape of the previous group. By adjusting the corresponding parameters, various expressible body shapes help in the dynamic generation of test data for a given behavior tested with several demographics. The combined values are relevant in ergonomics assessment, which aims to compute the physical workload a person must endure.

3) Social-Cognitives: This group contains the social and cognitive parameters relevant to human behavioral modeling, intention prediction, and artificial empathy. It consists of the modeled person's mood containing stress indication, the feeling of safety, mental fatigue regarding mental workload, and task motivation (flow). The mood also depends on the facial expression and emotional state, which can be modeled in several ways, like through an axis-based approach [29]. The same applies to the personality type. Furthermore, the template features an intention state consisting of the current goal state and the action and movement intent. Finally, the property group contains data on the simulated person's social situation. These indicators depend on other actors in a given scenario, like the social relation to (robotic) peers, robot awareness, acceptance and trust, etc.

4) Visualizationals: This group mainly contains the human 3D model. In general, (photo-)realistic representation in a DT is not necessarily required, even though this assumption might be subject to change when real people interact with the virtualization environment of a HDT also containing digitized humans. Two other properties are noteworthy: The authors of [30] describe a 3D level-of-detail, which expresses how detailed the visualization of the digitized person needs to be, allowing for dynamic adjustment for a given use case when implemented. Finally, the visualization group also contains information on the optical shape of the human, which is synthetically inferrable from the visualized 3D model or directly recorded from real-world persons. In computer vision applications, algorithms often work on 2D images of persons to infer knowledge. An example is the Region-based Convectional Neural Network in [31], which generates human optical shapes from a recorded image.

5) Sensorials: This group contains the data relevant to human sensory capabilities. The proposed template expresses a person's hearing and vision as these are most important for the targeted simulation applications of HRI. Regarding touch sensing, direct contact with robots is generally unfavorable, as it prevents the human actor from maintaining a social and minimum safe distance to the robot, which is why it is not present in the template. The modeled person's gaze digitally appears as a frustum based on eye movement, which results in a texture containing the perceived image. Computer vision applications for text or facial recognition can build on this data. Similarly, the perceived audio stored in audio files with a corresponding volume is usable for speech recognition or voice tone sensing.

IV. Finding model parameters and properties

This paper considered several recent works on applications of the HDT in social HRI simulations to find commonly applicable parameter groups for an abstracted digital human template. By taking a closer look at the human representation aspect of the corresponding work, properties, and parameters making up the digital human representation could be found and categorized into sets, similar to the "personal data" illustrated in [32] or the human model in [33]. This section provides a summary of the literature review used to discover human parameter categories for the HDT representation.

A. Literature review

Regarded papers originate from a Google Scholar search for works with a publication date from 2018 to 2024. Since this paper's focus lies specifically on simulations using the

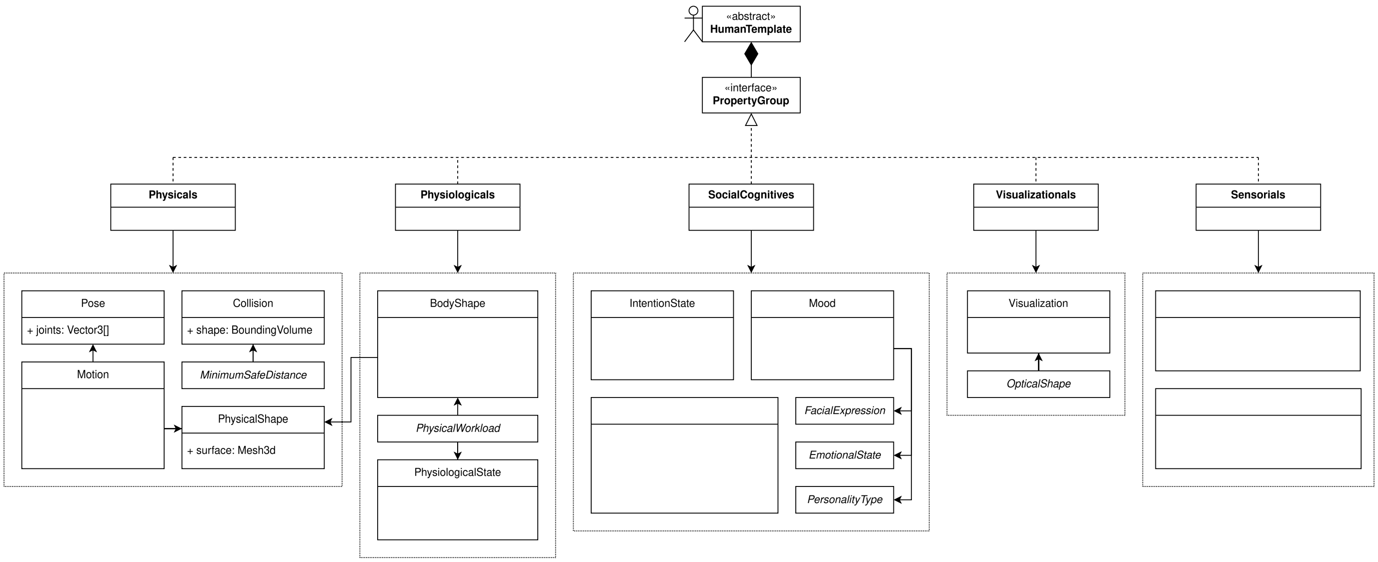

Fig. 2. Template of a digital human representation with digitized properties and parameters. *(Courtesy of CDM)*

DT approach for virtual validation of social robots, the search query contains the keyword groups ”human digital twin” or only ”digital twin” respectively. A second keyword group was added in the form of ”human-robot interaction” or ”human-robot collaboration” to ensure a relation to HRI. Ranking and filtering literature founded on relevance for DT applications and human digitization models in HRI based on their abstracts, regarding the first 20 listings. The review prioritized papers about HDT applications regarding the first 30 listings respectively. The result is 29 papers that contributed to the digital human template.

Table I gives an overview of the filtered work with a short summary of the included literature.

B. *Categorizing human properties and parameters*

Table II lists the discovered human model properties and parameters taken from the digital human representations. Each is present as a number indicating whether it falls into the category of **(1)** physical behavior, **(2)** physiological condition, **(3)** social-cognitive behavior, **(4)** visualization and finally **(5)** sensory capabilities. Note that the template assigns properties to the most fitting class. For instance: Even though a human pose can contain information about social-cognitive behavior, its raw representation originates from spatial-physical parameters. The impact of one set of parameters on another is not part of the template digitization, meaning they must be implemented separately through physical or behavioral models.

TABLE I.
LITERATURE OVERVIEW

Source	***Summary***
[6]	DT-based approach for designing flexible assembly systems
[7]	DT-based simulation of an HRI assembly cell
[8]	Presents a DT-framework for HRI collaborative work cells
[15]	DT system for effective scene mapping to virtual space
[20]	Techniques for HDT-driven cyber-physical systems
[21]	Preliminary human model for HDT
[23]	Proposes an assessment tool for HRI quality and well-being
[26]	DT for human/robot movement trajectory simulation
[30]	Proposes a generic HDT framework for human modelling
[31]	Mixed Reality visualization of min. safe dist.
[32]	Proposes a generic HDT framework for human modelling
[34]	DT-based ergonomics assessment using digital humans
[35]	DT of industrial workstation for synthetic data generation.
[36]	ML-enhanced reactive path planning for collision avoidance
[37]	Presents HDT-framework for safety and ergonomics models
[38]	DT & ML-based multi-modal scene reconstruction of HRI
[39]	Vision-based teleportation of robots based on human pose
[40]	Minimum safe distance calculated from machine vision
[41]	Proposes a generic DT/HDT architecture for HRI
[42]	Proposes a HDT architecture for Operator 4.0 applications
[43]	Ergonomics assessment using a digital human within a HDT
[44]	Intention predication through knowledge-based DT
[45]	Computer-vision-based safety decision making
[46]	HDT-architecture for human intention prediction
[47]	Collaborative task state based on human pose & motion
[48]	Vision-based DT system for robot control
[49]	HDT model to address human movement uncertainties
[50]	Proposes a HDT architecture based on multi-modal data
[51]	Remote control of robots through HDT-system

V. CONCLUSION

The paper proposed a template for digital human representation in DT-based simulations of social HRI. Categorized model properties and parameters form a sub-model, each represented through a property group. The variables contained per group originate from a literature review of recent work regarding DT-based approaches of social robot simulation. Looking at the discovered properties listed in Table II shows that most discovered variables appear more than once. An example several works consider regularly would be human pose estimation. The template given in section III includes the majority of discovered aspects. Data is only omitted if it is

TABLE II.
DIGITAL HUMAN MODEL PARAMETERS AND PROPERTIES

Source	***Digital Human Property / Parameter***
[6]	pose^1, motion^1, min. safe dist.^{1}, movement intention^3, robot awareness^3, interaction intention^3
[7]	pose^1, motion^1, min. safe dist.^{1}, 3D-model^4
[8]	collision^1, physical workload^2, 3D-model^4, gaze^5
[15]	pose^1, collision^1, min. safe dist.^{1}, interaction intention^2, 3D-model^4
[20]	pose^1, motion^1, heart rate^2, body temperature^2, physical workload^2, mood^3, interaction intention^3, 3D-model^4,
[21]	position^1, motion^1, personality^3, mood^3, emotion^3, motivation^3, relationship^3, biographical background^3, cognitive capability^3, interaction intention^3, desire/goal^3, speech recognition^5, vision^5, hearing^5, writing/reading^5, smelling^5
[23]	electrodermal activity^2, heart rate^2, pulsed blood volume^2, body temperature^2, stress^3,
[26]	min. safe dist.^{1}, motion^1, movement intention^2,
[30]	pose^1, motion^1, min. safe dist.^{1}, physical workload^2, blood pressure^2, heart rate^2, age^2, gender^2, BMI^2, stress^3, robot awareness^3, interaction intention^3, mood^3, mental fatigue^3, 3D-model^4, 3D-level-of-detail^4, hearing^5
[31]	pose^1, min. safe dist.^{1}, convex hull^1, optical shape^4
[32]	position^1, motion^1, body shape^{1,2}, heart rate^2, social identity^3, mood^3, 3D-model^4, optical shape^4
[34]	pose^1, motion^1, weight^2, height^2, gender^2, physical workload^2, movement intention^3
[35]	pose^1, motion^1, 3D-model^4
[36]	motion^1, bounding volume^1, min. safe dist.^{1}
[37]	position^1, motion^1, min. safe dist.^{1}, collision^1, age^2, bio-metric data^2, facial expression^3, safety^3, movement intention^3, personality^3, voice tone^3
[38]	pose^1, motion^1, body shapes^{1,2}, 3D-model^4
[39]	pose^1, motion^1, 3D-model^4
[40]	pose^1, motion^1, min. safe dist.^{1}, optical shape^4, 3D-model^4
[41]	motion^1, physical workload^2, movement intention^3, stress^3, safety^3, robot trust^3, robot acceptance^3
[42]	pose^1, motion^1, heart rate^2, blood pressure^2, speech recognition (hearing)^5, eye movement (gaze)^5
[43]	pose^1, motion^1, min. safe dist.^{1}, bounding box^1, weight^2, height^2, physical workload^2, 3D-model^4
[44]	pose^1, motion^1, interaction intention^3, 3D-model^4, gaze^5
[45]	bounding box^1, min. safe dist.^{1}, optical shape^4
[46]	pose^1, motion^1, movement intention^3, interaction intention^3, 3D-model^4,
[47]	pose^1, motion^1
[48]	pose^1, min. safe dist.^{1}, optical shape^4
[49]	pose^1, movement intention^3
[50]	pose^1, motion^1, plantar pressure^1, locomotion state^1, 3D-model^4
[51]	pose^1, motion^1

too specific for a general use case like pulsed blood volume or electrodermal activity as members of the physiological state. Since the template does not yet consider relations between parameters, it maintains simplicity focusing exclusively on the required properties making up a human representation.

VI. PROBLEMS AND FUTURE WORK

The previously described human digitization template does not include the relations of how parameters impact each other. This information needs to be featured in a future concrete implementation in form of physical and behavioral models. A proper use case would also require an underlying data model to properly represent the included human properties. The given default types are merely suggestions fitting to the parameter type, however, some aspects, especially cognitive states like robot awareness or trust, are likely to require a more fleshed-out representation. Lastly, categorization can be difficult for specific aspects. An example would be facial expressions, which can be seen as a physiological state, a visualization problem and digitized data on the represented person's mood. Categorization, however, helps in structuring the many aspects of human modelling, which is this paper's main contribution.

REFERENCES

[1] Y. Yan and Y. Jia, "A review on human comfort factors, measurements, and improvements in human–robot collaboration," *Sensors*, vol. 22, no. 19, 2022.

[2] M. Javaid, A. Haleem, and R. Suman, "Digital Twin applications toward Industry 4.0: A Review," *Cognitive Robotics*, vol. 3, pp. 71–92, Jan. 2023.

[3] F. Pires, A. Cachada, J. Barbosa, A. P. Moreira, and P. Leitao, "Digital Twin in Industry 4.0: Technologies, Applications and Challenges," in *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)*, (Helsinki, Finland), pp. 721–726, IEEE, July 2019.

[4] Y. Liu, L. Zhang, Y. Yang, L. Zhou, L. Ren, F. Wang, R. Liu, Z. Pang, and M. J. Deen, "A Novel Cloud-Based Framework for the Elderly Healthcare Services Using Digital Twin," *IEEE Access*, vol. 7, pp. 49088–49101, 2019.

[5] T. Erol, A. F. Mendi, and D. Dogan, "The Digital Twin Revolution in Healthcare," in *2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, (Istanbul, Turkey), pp. 1–7, IEEE, Oct. 2020.

[6] N. Kousi, C. Gkournelos, S. Aivaliotis, K. Lotsaris, A. C. Bavelos, P. Baris, G. Michalos, and S. Makris, "Digital Twin for Designing and Reconfiguring Human–Robot Collaborative Assembly Lines," *Applied Sciences*, vol. 11, p. 4620, May 2021. Number: 10 Publisher: Multidisciplinary Digital Publishing Institute.

[7] A. Bilberg and A. A. Malik, "Digital twin driven human–robot collaborative assembly," *CIRP Annals*, vol. 68, no. 1, pp. 499–502, 2019.

[8] A. A. Malik and A. Bilberg, "Digital twins of human robot collaboration in a production setting," *Procedia Manufacturing*, vol. 17, pp. 278–285, Jan. 2018.

[9] N. Stojanovic and D. Milenovic, "Data-driven digital twin approach for process optimization: an industry use case," in *2018 IEEE International Conference on Big Data (Big Data)*, pp. 4202–4211, 2018.

[10] C. Semeraro, M. Lezoche, H. Panetto, and M. Dassisti, "Digital twin paradigm: A systematic literature review," *Computers in Industry*, vol. 130, p. 103469, 2021.

[11] B. Ashtari Talkhestani, T. Jung, B. Lindemann, N. Sahlab, N. Jazdi, W. Schloegl, and M. Weyrich, "An architecture of an Intelligent Digital Twin in a Cyber-Physical Production System," *at - Automatisierungstechnik*, vol. 67, pp. 762–782, Sept. 2019.

[12] M. Lindner, L. Bank, J. Schilp, and M. Weigold, "Digital Twins in Manufacturing: A RAMI 4.0 Compliant Concept," *Sci*, vol. 5, p. 40, Oct. 2023. Number: 4 Publisher: Multidisciplinary Digital Publishing Institute.

[13] M. Dassisti and C. Semeraro, "Smart Sustainable Manufacturing: a new Laboratory-Factory concept to test Industry 4.0 principles," in *8th International Conference on Information Society and Technology, ICIST 2018*, (Kopaonik, Serbia), Mar. 2018.

[14] D. Sparrow, K. Kruger, and A. Basson, "Human Digital Twin for Integrating Human Workers in Industry 4.0," in *2019 COMA '19 International Conference on Competitive Manufacturing*, pp. 259–265, 2019.

[15] Z. Zhang, Y. Ji, D. Tang, J. Chen, and C. Liu, "Enabling collaborative assembly between humans and robots using a digital twin system," *Robotics and Computer-Integrated Manufacturing*, vol. 86, p. 102691, Apr. 2024.

[16] Y. Lin, L. Chen, A. Ali, C. Nugent, C. Ian, R. Li, D. Gao, H. Wang, Y. Wang, and H. Ning, "Human Digital Twin: A Survey," Dec. 2022. arXiv:2212.05937 [cs].

[17] M. E. Miller and E. Spatz, "A unified view of a human digital twin," *Human-Intelligent Systems Integration*, vol. 4, pp. 23–33, Mar. 2022.

[18] W. Shengli, "Is Human Digital Twin possible?," *Computer Methods and Programs in Biomedicine Update*, vol. 1, p. 100014, 2021.

[19] T. Bergs, S. Gierlings, T. Auerbach, A. Klink, D. Schraknepper, and T. Augspurger, "The concept of digital twin and digital shadow in manufacturing," *Procedia CIRP*, vol. 101, pp. 81–84, 2021. 9th CIRP Conference on High Performance Cutting.

[20] B. Wang, H. Zhou, G. Yang, X. Li, and H. Yang, "Human Digital Twin (HDT) Driven Human-Cyber-Physical Systems: Key Technologies and Applications," *Chinese Journal of Mechanical Engineering*, vol. 35, p. 11, Feb. 2022.

[21] Y. Naudet, A. Baudet, and M. Risse, "Human Digital Twin in Industry 4.0: Concept and Preliminary Model:," in *Proceedings of the 2nd International Conference on Innovative Intelligent Industrial Production and Logistics*, pp. 137–144, SCITEPRESS - Science and Technology Publications, 2021.

[22] T. B. Sheridan, "A review of recent research in social robotics," *Current Opinion in Psychology*, vol. 36, pp. 7–12, 2020. Cyberpsychology.

[23] E. Verna, S. Puttero, G. Genta, and M. Galetto, "A Novel Diagnostic Tool for Human-Centric Quality Monitoring in Human–Robot Collaboration Manufacturing," *Journal of Manufacturing Science and Engineering*, vol. 145, Sept. 2023.

[24] A. Martínez, L. M. Belmonte, A. S. García, A. Fernández-Caballero, and R. Morales, "Facial Emotion Recognition from an Unmanned Flying Social Robot for Home Care of Dependent People," *Electronics*, vol. 10, p. 868, Apr. 2021. Number: 7 Publisher: Multidisciplinary Digital Publishing Institute.

[25] T. Smith, Y. Chen, N. Hewitt, B. Hu, and Y. Gu, "Socially Aware Robot Obstacle Avoidance Considering Human Intention and Preferences," *International Journal of Social Robotics*, vol. 15, pp. 661–678, July 2023.

[26] Y. Fukushima, Y. Asai, S. Aoki, T. Yonezawa, and N. Kawaguchi, "DigiMobot: Digital Twin for Human-Robot Collaboration in Indoor Environments," in *2021 IEEE Intelligent Vehicles Symposium (IV)*, pp. 55–62, July 2021.

[27] D. Koert, J. Pajarinen, A. Schotschneider, S. Trick, C. Rothkopf, and J. Peters, "Learning Intention Aware Online Adaptation of Movement Primitives," *IEEE Robotics and Automation Letters*, vol. 4, pp. 3719–3726, Oct. 2019.

[28] L. Gazzaneo, A. Padovano, and S. Umbrello, "Designing Smart Operator 4.0 for Human Values: A Value Sensitive Design Approach," *Procedia Manufacturing*, vol. 42, pp. 219–226, Jan. 2020.

[29] A. Mehrabian, "Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in Temperament," *Current Psychology*, vol. 14, pp. 261–292, Dec. 1996.

[30] Q. He, L. Li, D. Li, T. Peng, X. Zhang, Y. Cai, X. Zhang, and R. Tang, "From Digital Human Modeling to Human Digital Twin: Framework and Perspectives in Human Factors," *Chinese Journal of Mechanical Engineering*, vol. 37, p. 9, Feb. 2024.

[31] S. H. Choi, K.-B. Park, D. H. Roh, J. Y. Lee, M. Mohammed, Y. Ghasemi, and H. Jeong, "An integrated mixed reality system for safety-aware human-robot collaboration using deep learning and digital twin generation," *Robotics and Computer-Integrated Manufacturing*, vol. 73, p. 102258, Feb. 2022.

[32] Y. W. Song, "Human Digital Twin, the Development and Impact on Design," *Journal of Computing and Information Science in Engineering*, vol. 23, Aug. 2023.

[33] X. Ma, Q. Qi, J. Cheng, and F. Tao, "A consistency method for digital twin model of human-robot collaboration," *Journal of Manufacturing Systems*, vol. 65, pp. 550–563, Oct. 2022.

[34] S. Baskaran, F. A. Niaki, M. Tomaszewski, J. S. Gill, Y. Chen, Y. Jia, L. Mears, and V. Krovi, "Digital Human and Robot Simulation in Automotive Assembly using Siemens Process Simulate: A Feasibility Study," *Procedia Manufacturing*, vol. 34, pp. 986–994, Jan. 2019.

[35] M. Dallel, V. Havard, Y. Dupuis, and D. Baudry, "Digital twin of an industrial workstation: A novel method of an auto-labeled data generator using virtual reality for human action recognition in the context of human–robot collaboration," *Engineering Applications of Artificial Intelligence*, vol. 118, p. 105655, Feb. 2023.

[36] K. Dröder, P. Bobka, T. Germann, F. Gabriel, and F. Dietrich, "A Machine Learning-Enhanced Digital Twin Approach for Human-Robot-Collaboration," *Procedia CIRP*, vol. 76, pp. 187–192, Jan. 2018.

[37] B. Gaffinet, J. A. H. Ali, H. Panetto, and Y. Naudet, "Human-Centric Digital Twins: Advancing Safety and Ergonomics in Human-Robot Collaboration," in *Innovative Intelligent Industrial Production and Logistics* (S. Terzi, K. Madani, O. Gusikhin, and H. Panetto, eds.), (Cham), pp. 380–397, Springer Nature Switzerland, 2023.

[38] Y. Ji, Z. Zhang, D. Tang, C. Liu, Z. Zhao, and Q. Cao, "A Multi-modal Construction Method for a Digital Twin System with Human-Robot Collaboration," in *2023 8th International Conference on Control, Robotics and Cybernetics (CRC)*, (Changsha, China), pp. 92–96, IEEE, Dec. 2024.

[39] H. Lee, S. D. Kim, and M. A. U. A. Amin, "Control framework for collaborative robot using imitation learning-based teleoperation from human digital twin to robot digital twin," *Mechatronics*, vol. 85, p. 102833, Aug. 2022.

[40] H. Li, W. Ma, H. Wang, G. Liu, X. Wen, Y. Zhang, M. Yang, G. Luo, G. Xie, and C. Sun, "A framework and method for Human-Robot cooperative safe control based on digital twin," *Advanced Engineering Informatics*, vol. 53, p. 101701, Aug. 2022.

[41] X. Lu, X. Li, W. Wang, K.-M. Chao, L. Xu, P. De Vrieze, and Y. Jing, "A generic and modularized Digital twin enabled human-robot collaboration," in *2022 IEEE International Conference on e-Business Engineering (ICEBE)*, pp. 66–73, Oct. 2022.

[42] A. Löcklin, T. Jung, N. Jazdi, T. Ruppert, and M. Weyrich, "Architecture of a Human-Digital Twin as Common Interface for Operator 4.0 Applications," *Procedia CIRP*, vol. 104, pp. 458–463, Jan. 2021.

[43] T. Maruyama, T. Ueshiba, M. Tada, H. Toda, Y. Endo, Y. Domae, Y. Nakabo, T. Mori, and K. Suita, "Digital Twin-Driven Human Robot Collaboration Using a Digital Human," *Sensors*, vol. 21, p. 8266, Dec. 2021. Number: 24 Publisher: Multidisciplinary Digital Publishing Institute.

[44] T. B. Tuli, L. Kohl, S. A. Chala, M. Manns, and F. Ansari, "Knowledge-Based Digital Twin for Predicting Interactions in Human-Robot Collaboration," in *2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, pp. 1–8, Sept. 2021.

[45] S. Wang, J. Zhang, P. Wang, J. Law, R. Calinescu, and L. Mihaylova, "A deep learning-enhanced Digital Twin framework for improving safety and reliability in human–robot collaborative manufacturing," *Robotics and Computer-Integrated Manufacturing*, vol. 85, p. 102608, Feb. 2024.

[46] B. Yao, B. Yang, W. Xu, Z. Ji, Z. Zhou, and L. Wang, "Virtual data generation for human intention prediction based on digital modeling of human-robot collaboration," *Robotics and Computer-Integrated Manufacturing*, vol. 87, p. 102714, Dec. 2023.

[47] Z. Ye, L. Jingyu, and Y. Hongwei, "A digital twin-based human-robot collaborative system for the assembly of complex-shaped architectures," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, Aug. 2022.

[48] S. Yi, S. Liu, X. Xu, X. V. Wang, S. Yan, and L. Wang, "A vision-based human-robot collaborative system for digital twin," *Procedia CIRP*, vol. 107, pp. 552–557, 2022.

[49] P. Zheng, S. Li, J. Fan, C. Li, and L. Wang, "A collaborative intelligence-based approach for handling human-robot collaboration uncertainties," *CIRP Annals*, vol. 72, pp. 1–4, Jan. 2023.

[50] R. Zhong, B. Hu, Y. Feng, H. Zheng, Z. Hong, S. Lou, and J. Tan, "Construction of Human Digital Twin Model Based on Multimodal Data and Its Application in Locomotion Mode Identification," *Chinese Journal of Mechanical Engineering*, vol. 36, p. 126, Oct. 2023.

[51] H. Zhou, H. Lv, R. Wang, H. Wu, and G. Yang, "Revitalizing Human-Robot Interaction: Phygital Twin Driven Robot Avatar for China–Sweden Teleoperation," *Chinese Journal of Mechanical Engineering*, vol. 36, p. 124, Oct. 2023.