Human Digital Twin in Industry 4.0: Concept and Preliminary Model

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Keywords: Digital Twin, Human Model.

Abstract: Digital Twins originally concern technical systems and do not yet integrate human elements properly. This limits their quality and usefulness when we consider systems where machines and human workers still cohabit. This paper presents the concept of Human Digital Twin (HDT), the human equivalent of a Digital Twin (DT), which aim at being coupled with DTs of technical elements in systems where humans play a role. We detail the state of the art on the subject, propose a definition for HDT and a preliminary human model, bringing foundations for handling the human factor in industry with digital twins.

1 INTRODUCTION

The Digital Twin (DT) concept originates from the aerospace field, with premises around 2003, according to (Tao et al., 2019), and a first publication in 2010 (Shafto et al., 2010). It is now an important keyword in the domains of Industry 4.0, Factory of the Future and Smart Factory. According to (Negri et al., 2017), research on the DT in manufacturing is an evolution of the research stream about Virtual Factories.

There is still no common definition of what a Digital Twin is. (Negri et al., 2017) reports 16 different definitions from 2010 to 2016 mainly in the aerospace and manufacturing fields. According to the authors, a Digital Twin "*provides a virtual representation of a system along its life-cycle*", where "*optimizations and decision-making would then rely on the same data that are updated in real-time with the physical system*". This is further refined in: "*The Digital Twin is meant as the virtual and computerized counterpart of a physical system that can be used to simulate it for various purposes, exploiting a real-time synchronization of the sensed data coming from the field*".

But as digital representation of our world are created with the hype on digital twins, they focus on virtual representations of human-built systems (e.g. factories, cities, buildings, machines...) and tend to forget the essential element: human-beings. Actually, be it objects or environments, all have some kind of interaction with humans: objects are used by humans and environments are spaces where objects and humans cohabit and can have interactions. With the Internet of Things and the progress in Artificial Intelligence (AI), among other technologies, we have seen the emergence of the so-called smart things, or smart systems if we take a generic perspective, including smart objects and smart environments. This smartness can take different forms and be implemented in many ways, but it will never be really smart if the central variable is forgotten. Finally smart systems are designed to support humans in the best possible way, and reaching this objective without having an understanding of humans needs or humans themselves is probably not optimal for the human-smart system interaction. In this perspective, AI needs models of humans whatever their form and scope, and digital twins of smart systems need also models that represent digitally the humans they interact with or that they contain. This is where we introduce the concept of the Human Digital Twin (HDT), which emerged in our discussions about digital twin in 2019, and at the same time in the heads of other researchers as we will show in the next section.

2 STATE OF THE ART

The oldest reference to the concept of Human Digital Twin comes from the health sector, where it is conceived as a sophisticated simulation of the human body (Blake, 2016). Today, only some small parts of the human body can be modelled to run simulation of treatments (e.g. arthritis in the knee), and the complexity of the human body is still too high for our understanding to build a complete model. However, technological advances in 3D scanning, wearable IOT

Naudet, Y., Baudet, A. and Risse, M.
Human Digital Twin in Industry 4.0: Concept and Preliminary Model.
DOI: 10.5220/0010709000003062
In *Proceedings of the 2nd International Conference on Innovative Intelligent Industrial Production and Logistics (IN4PL 2021)*, pages 137-144
ISBN: 978-989-758-535-7

and AI allow already high precision and near real-time modelling of more and more complex parts.

Taking a generic perspective applicable to any smart system, Hafez introduces the HDT as a "*human-specific smart machine dedicated to aligning human objectives with the smart machines supporting her*". His approach focuses on finding recurrent human-machine interaction patterns to maintain this alignment by anticipating human responses in given contexts (Hafez, 2020). (Zibuschka et al., 2020) build on this view, and characterise the HDT according to the C2PS (Cloud-based Cyber-Physical System) reference architecture for DT (Alam and El Saddik, 2017). It is then defined as a technical system comprising virtual sensors gathering observations about one or several humans, functional units focusing on behavior analysis which derive knowledge about users. The authors highlight smart home, building and office as application field and emphasize the interest for identity management and data protection.

2.1 Related Approaches

In computer ergonomics, *Digital Human Modelling* (DHM) refers to a human model as a 3D representation of a human including anthropometric and kinematic aspects ((Case et al., 2016)), used especially in inclusive engineering (3D) design since around 1972. In short, DHM build virtual humans that are realistic 3D representations in motion, based on data gathered from extensive surveys on human populations and completed now by 3D scanned templates of the human body. DHM can certainly be considered as a basis for building HDT, from the 3D representation perspective. Originally in this field, the knowledge of user behaviour characterising real people and linked to their physiological or psychological characteristics (e.g. mood, fatigue, stress) is left to the ergonomist, and not yet embedded in the human model. However, embedding further cognitive, behavioural or emotional human characteristics is one of the research tracks for design tools identified by (Case et al., 2016), which shows some convergence with the needs of a HDT.

The *Personal Digital Twin* (PDT) is another concept similar to HDT, introduced in 2020 (Saracco et al., 2020) as a solution to tracking needs and pandemics control induced by the Covid-19 crisis and for personalized healthcare. The PDT is defined as a "*representation of various aspects of a person that might include the movement of the person, the interactions that person has in physical space with other people, and her health status*". Through the observations from the sensors embedded in personal mobile devices (e.g. smartphones and wearables), the goal is to digitize physical persons, and thus creating their DT, to "*enable anonymous and secure sensing, collection and analysis of data to inform strategic decisions that can disrupt the current ways the healthcare system works and manages pandemic situations*". The authors further emphasize that it can be used to create virtual social spaces where PDT are connected together, able to share data and seek for advice from others. PDT also can act as personal assistant and proxy to medical authorities, in a networked environment where PDT manage personal data, can reason from local context, interact with other PDT, with the health system and central authorities. The advantages for predictive analysis, awareness transmission and problems (here, crisis) prevention are clear, as well as the induced privacy concerns related to the anytime tracking of persons and their consent to share personal data.

2.2 On the Web

HDT is the subject of an anonymous blog at *humandigitaltwin.com*[1] dated from May 2020. The author refers to having a human model including any sort of data related to a person and its experience, that could be clustered according to six dimensions: physical, cognitive, emotional, social, occupational and financial. Here, the concept relates to data sovereignty and originates from the idea that humans should own and operate data they produce in the digital world, and thus stay in control of their *digital self*, which is unfortunately not the case today. Finally, HDT is foreseen technically as a human model, analytic functions allowing to process the data from the model and a user interface (including a dashboard) to access and control data and processing analytics results.

Avenga Labs refers to HDT as *digital twins of people*, which are digital representations of humans as complex physical objects[2]. The link to digital activities and related data is also made, referring to the *digital shadow* of a person, and the privacy concerns this induces. Another company, Proglove, advertises largely the HDT, presented as the digital counterpart of the human worker and introduced also as the missing representation of humans in Industry 4.0 Digital Twins[3]. They present wearables as the enabling technology for building HDTs, to gather data about workers in supply chains, as a necessary tool providing ac-

[1] https://www.humandigitaltwin.com/

[2] https://www.avenga.com/magazine/human-digital-twins/

[3] https://itsupplychain.com/human-digital-twin-the-digital-counterpart-to-the-human-worker/

tionable insights to deal with unexpected potentially complex situations[4]. This is referred also by the Picavi company in the logistics sector, as a representation of a human being resulting from the tracking of its activities [5]. It is used for analytics, process improvement and training.

Finally, several references can be found in the health sector, comprising dedicated research centers. We can cite the Semic RF company, proposing a product called Digital Body Total, which is a digital replica of a human's being organs and biological or molecular systems, embedding AI [6]. Originally called Cyber Bio Twin [7], it aim at providing a framework for medical diagnosis, experimentation, predictions and support for clinical trials and decision-making. In academy, the Geriatronics initiative of the MSRM research center of the Technical University of Munich works on a HDT for personalised diagnostics, which is a humanoid DT able to create a real-time visualization of the physiological processes within the body [8]. Last, the OnePlanet research center in Netherlands refers to the HDT as a data-driven digital platform that collects data related to an individual's health and nutrition, and analyses it to provide personalised advices on diet, lifestyle and medicines [9].

2.3 In Industry

Because Industry 4.0 has been focusing a lot on digitalisation, human factors are not often considered within researches on Digital Twin. So far, workers were seen more as spectators than actors (Peruzzini et al., 2018, citing (Hermann, Pentek, & Otto, 2017)), but they should instead be considered as part of the intelligent system, where they can generate data for machine programming and processes optimisation while benefiting from inputs and "*collaboration with smart systems*" (Peruzzini et al., 2018). In this work, the authors experiment a human-centred approach to industrial systems, where they include human-related data in the Digital Twin of a factory. Although efforts are done to account for human factors in the factory of the future, see e.g, (Longo et al., 2019), which we detail in section 3, these are not yet integrated with the DT. Indeed in a recent review on Digital Twin for smart manufacturing highlights *Digital Twin for people* as a research challenge, considering humans are not yet considered as integral parts of the smart manufacturing system (Lu et al., 2020). Modelling humans is expected to help understanding personal wellbeing and working conditions, designing human-centred human-machine collaboration taking into account physical and physiological factors in the production optimisation process, and allow building personalised virtual training.

(Nikolakis et al., 2019) addresses the digital twin of manual (human-centred) operations, implemented as a part of a Cyber-Physical System observing and controlling the shop floor for optimising human-based production thanks to simulations. In this context, the DT integrates both the human operator and its environment, but a proper digital human modelling approach integrating human-specific factors is essential. Based on this, simulations can be used to improve at the same time the production quality and the ergonomics of human-centred operations. To go a step further than using kinematics-based models, the authors gather real-time observations of the human worker behaviour through motion capture, recording operations and attaching motion patterns and constraints to tasks. This allows then to make more realistic simulations in a 3D environment, where the human model behaves according to a motion model implemented from in-situ operations, highlighting in particular what should be adapted in the physical working space configuration. Implemented in a closed control loop, this ultimately leads to shopfloor reconfiguration for optimised production quality and ergonomics, without the need to interrupt the production process.

(Baskaran et al., 2019) highlight the need to represent both human and machine elements in DT of industrial processes. They implement the HDT as a 3D model of human workers to simulate a manufacturing process with human-robot interaction. The model includes biomechanical, anthropometric and ergonomics characteristics allowing to simulate human average behaviours validated and standardised by field studies. This HDT approach is used to study the ergonomic impact in what-if scenarios using a digital manufacturing simulation tool. HDT is introduced as a "*human digital model implementing a near-real time digital image of a physical human in a virtual environment*". Indeed, Human-Robot Collaboration (HRC) is one of the main application fields where digital representations of humans are useful, whatever their form. In (Lu et al., 2020), virtual simulations models are used to dynamically allocate and coordinate tasks between human and robot, based on their skills and state, respecting the best workload balancing. The observation of human behaviour com-

[4] https://www.proglove.com/blog/digital-twin/human-digital-twins-boost-actionable-insights/

[5] https://picavi.com/en/human-digital-twin-productive-onboarding-for-new-employees/

[6] https://semic.de/en/ai/semic-health

[7] https://www.cyberbiotwin.com/

[8] https://geriatronics.msrm.tum.de/human-digital-twin/

[9] https://oneplanetresearch.nl/innovatie/digital-twin/

pared to a reference allows the robot to adapt its behaviour to human factors affecting the work quality or the task duration (e.g. skill level, motivation, failure sensitivity for complex processes).

3 THE HDT CONCEPT

3.1 Definition

We introduce here a generic definition of the Human Digital Twin, as a specific DT dedicated to humans:

Definition (Human Digital Twin)**.** *A Human Digital Twin (HDT) is a subclass of the Digital Twin whose particularity lies in the human nature of the twinned entity. It is a real-time mirroring computerized system of a human agent, able to simulate or emulate his characteristics and behavior in context.*

To some extent, an HDT would be based on the same general principles than a classical DT, except the substantial difference that the twined physical system consists of a human agent. Therefore, the HDT can be considered as a subclass of DT, inheriting from all its properties, but which also implies to take some specifications into account during all conceptualization, modeling, implementation and maintenance phases. The HDT should be familiar with tasks' short and long term objectives of its physical twin, and integrates some AI-based tools to analyse incoming physical and physiological data, and to provide predictive operations. As synchronized states mirroring and updating remain primary stakes, the HDT implementation must be articulated around real-time data gathering from the human entity. Where this task do not seems to show major difficulties with non-human agents, continuously measuring human physical and physiological data and transforming them into significant and actionable knowledge reveals much more impediments. But before all, the HDT needs to rely on a proper human model, enough close to reality to allow simulation and possibly emulation.

3.2 Virtual Human

A starting point for conceiving a (structural and behavioural, in contract to a visual representation like in DHM) human model for a HDT can be to look at the concept of *Virtual Human*, to which a book is dedicated (Burden and Savin-Baden, 2019). Summarising from the multiple views and definitions from the literature, authors define virtual humans as "*Software programs which present as human and which may have behavior, emotion, thinking, autonomy and interaction modelled on physical human capabilities*". The concept is the averaged view representing systems ranging from simple virtual humans that enact only partially, in a simplistic way the listed properties, to *Virtual Sapiens*: "*Sophisticated virtual humans which achieve similar levels of presentation, behavior, emotion, thinking, autonomy, interaction, self-awareness and internal narrative to a physical human*".

(Burden and Savin-Baden, 2019) propose a model for virtual human, based on one mandatory characteristic -it is virtual-, and ten traits that characterise also human-beings: (1) *embodiment* (physical or virtual); (2) *humanity* (humanoid or not); (3) *natural language communication*; (4) *autonomy*; (5) *emotion* (demonstrating and responding to); (6) *personality* (own specific behaviour); (7) *reasoning*; (8) *learning*; (9) *imagination*; and (10) *self-awareness* (linked to sentience at the extreme). Virtual humans can be defined according to the proportion of this traits they have, with at the boundaries the virtual humanoid (lower bound, which has only very basic characteristics) and the virtual sapiens, who has all the traits at full level.

3.3 Human Factors in Industry 4.0

In 2019, an extensive work has been done on defining a taxonomy of human factors, encompassing all the capabilities of industrial workers influencing their work (Longo et al., 2019). Factors are classified according to three spheres of capabilities, namely *cognitive*, *physical* and *psychological*, which are divided in traits, themselves divided in facets. In total, there are 11 traits and 50 facets. This taxonomy provide a big set of characteristics that can be included in a human model. However this is only a basis. Indeed to build a model allowing to simulate/emulate human behaviour, the way each of these characteristics work and influence each other should be sought in relevant theories. In the following we detail the main factors and highlight the theories we think the most relevant.

3.4 Relevant Factors and Models

If several ways are possible to model a virtual human or a HDT, cognitive architectures constitute probably a highly relevant one. As explained in (Lieto et al., 2018), using cognitive architectures indicates "*both abstract models of cognition, in natural and artificial agents, and the software instantiations of such models*". Psychology and computer sciences were the pioneering sciences to consider human user in a cognitive architecture context. With more than estimated

300 cognitive architectures, the application domains and variables of each architecture are varied and heterogeneous. Briefly, most of the cognitive architectures are focused on one or several of the following core cognitive abilities or capabilities: *perception*, *attention*, *action selection*, *memory*, *learning*, *reasoning* and *metacognition* (Kotseruba and Tsotsos, 2020). Most of those capabilities are present in virtual humans. Learning and memory are considered together in the virtual human model, perception-attention-action is linked to autonomy, and metacognition can be mapped to imagination.

One of the most known model implementing part of these cognitive abilities is certainly BDI (Belief, Desire, Intention), which is used since years by the Multi-Agent-Systems community. BDI agents are generally characterized by affective states such as emotions, mood or personality but sometimes also by affective capacities such as empathy or emotional regulation (Sánchez-López and Cerezo, 2019). Discussing on how to model human social behaviour in agent-based systems, (Kennedy, 2012) list a set of basic principles to implement: human ability to *process sensory information*; *personality*; *motivations and needs*; *rationality* and the ability to *represent knowledge*, *learn*, *memorize and act* according to this knowledge); *emotions*, leading to intuitive and unconscious decision-making; and in social behaviour the *imagination about others behaviour* (theory of Mind) and its influence on self-behaviour. The author drives to BDI, but also PECS (Physical, Emotional, Cognitive and Social factors) and "fast and frugal decision hierarchies" conceptual frameworks for agents on one side, and on the other side to cognitive architectures like Soar and ACT-R (see the book chapter for references).

Another example of human behaviour simulation by a software agent can be found in (Kamara-Esteban et al., 2017), where the human agent implements a behaviour model following the *Behaviour*, *Activity*, *Action* principle, where behaviour is defined by an activity that consists in a set of consecutive actions. As a core human ability, action selection is the process of "what" has to be decided and "how" to decide it. Several factors – relevance, utility and internal factors - have an impact on the "next" action, but the main variance of a behaviour is mostly determined by internal factors, which are key in cognitive architectures (Kotseruba and Tsotsos, 2020), but also in human-computer interaction, social robotics and virtual agents. Whatever the model or architecture and the set of abilities considered, these factors are the most important.

Internal factors of a human are intangible forces that may cause, moderate or increase a response to an event. When they are considered, there are at least three main interdependent determinants to get a faithful model, which we detail here: *personality*, *desire*, and *emotions*.

- **Personality**, as a relatively stable variable (Costa and McCrae, 1988) in most cultures in the world, can help to predict and model patterns of behavior. With the Five Factor Model and Big 5 theory, personality is broken down into 5 main dimensions (Openness, Conscientiousness, Extraversion, Agreeability, Nevrosism) and depending on the assessment tool into 30 traits. Following several combinations of personality dimensions and emotions, typical reactions can be predicted (Shvo et al., 2019). Since decades, personality, in addition to intelligence (also called cognitive ability or g factor), are the two biggest predictors of job performance and training efficiency, whatever the job, as shown in thousand of studies, e.g., (Schmidt and Hunter, 1998).
- **Desire or Motivation** is also a key determinant of a human behavior. In several cognitive architectures, preservation drives, curiosity or interaction drives are examples of modelled drives. To easily draw the inter-dependencies with emotions and personality, we consider that the Reiss 16 desires model could be relevant as suggested by (Shvo et al., 2019). Any behavior is usually executed to satiate one or more basic desires (e.g. power, curiosity, social contact, saving, etc) and the human user has always to choose which drive is priority.
- **Emotions**, unlike personality, have a transient nature. Like motivation, several emotion models exist. Russell's circumflex model of affect (Russell, 1980), firstly proposed in 1980, instigated a lot of progress and innovation for emotion understanding and comprehension. This model allows to reference 28 emotion-denoting adjectives, spatially represented in a two-dimensional circle, depending on the arousal and valence levels to which they are associated. Today, the OCC theory (Ortony et al., 1990) is one of the most used. It is composed of 21 emotions (joy, distress, fear, anger, love, hate, etc.) with several levels (primary, secondary, tertiary). For an innate or primary emotion (e.g. love), a human may feel a secondary emotion (e.g. affection) and then as consequence of the secondary emotion, a tertiary emotion (e.g. tenderness).

In addition to the choice of models for every internal force, the literature showed that the inter-dependencies between each force is also a challenge in terms of modelling (Sánchez-López and Cerezo, 2019). To implement a HDT, the first challenge is to rely on a proper model of human, modelling each internal state together with their dependencies. A good candidate can be found in (Shvo et al., 2019), where *Emotion*, *Motivation*, *Personality* and *Mood* are taken together with the *State* of an entity as inputs for defining an action scheduler. In this model, each variable is defined from known theories and combined with attention on regulation and feedback loops.

4 OUR HDT MODEL

Industrial 4.0 settings can be digitized according to one single DT, or a set of different DT connected together, representing different departments, shop floors, machines or other systems. The first case does not fit to HDT, because humans are considered like other entities, from the influence they have on the overall system that is twinned. We consider the second approach, each time it make sense to have DTs of individual elements, or entities, contributing to a same objective. In a shop floor, this would be machines, robots and humans involved in production tasks.

Following our definition, the HDT can be designed as a subclass of DT, where the twinned physical entity is a human being. We have formalised an architectural model, taking an information-centric perspective based on the interactions between the physical system - that can also be referred to as "Physical Twin" (PT)- and the DT. In this model, the DT is itself lying on interconnections between synchronization, data management, and services layers, and a mediator component manages the information exchanges between these layers. We show in Figure 1 only the parts that are relevant for the purpose of this paper. *Physical Entity* refers to a physical entity that is virtually mirrored and is the target of the twinning objectives. It can be a *Human Agent* or *Non-Human Agent*, and performs some *Tasks* in an *Environment* where other entities evolve and with which it is in relation. The physical entity is coupled with a *Digital Twin*, which as a mirror of the physical space can also be a Human Digital Twin or a Non-Human Digital Twin. In this paper, our focus is the *Internal Model* concept, representing the set of models embedded in a DT, and more specifically the *Entity Model*, which in the case of a HDT is the model of a twinned human.

The HDT's entity model constitutes one of the most challenging aspects, and it will often be limited to the intended HDT's scope. However, it remains important to have a good awareness of all the human characteristics, to be sure neglected variables can actually be neglected in each use-case. In industry, one of the objectives supported by the HDT would be to allow a certain level of production (quality, quantity) combining well-being of workers and performance. This implies in particular taking into account components of emotion through the detection of physiological signals. Fatigue anticipation is one of the common example. Another one is the detection of a detrimental level of stress, or any other factor leading to an increase in error occurrences probability. But the other dimensions can not be neglected: motivation variations, associated to the personality have also an impact on productivity as well as the physical state of the human worker.

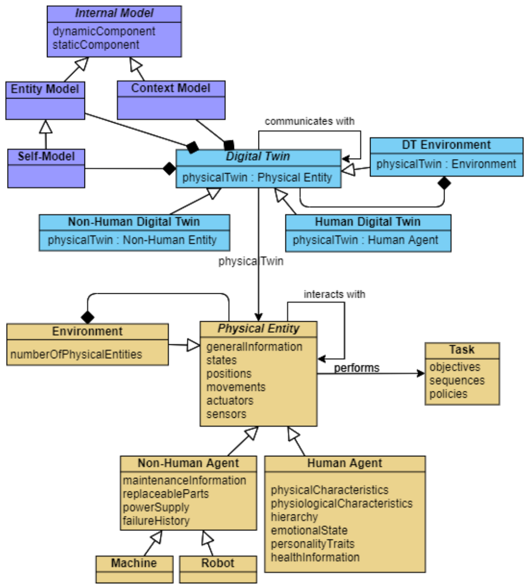

Figure 1: Conceptual Model of DT and HDT concepts.

We propose a preliminary (meta-)model of human in Figure 2, relevant for simulating humans at work with a HDT. It presents the main human characteristics, abilities and states of a *human agent* in context, performing a task according to a given demand, and the influential links between the different variables impacting the worker behaviour. The main elements from the works retained from the state of the art are present, especially the three spheres of (Longo et al., 2019), *Belief*, *Desire* and *Intention* elements and the psychological characteristics driving the internal forces that will impact behaviour: *Personality*, *Emotion*, *Motivation*, completed by *Mood* to account for the work of (Shvo et al., 2019). In its current state, the model focuses on variables influencing the *emotional state*, and highlights the relevant theories and models for each of the main ones. Variables driving the *physical state* are also modelled, but not detailed.

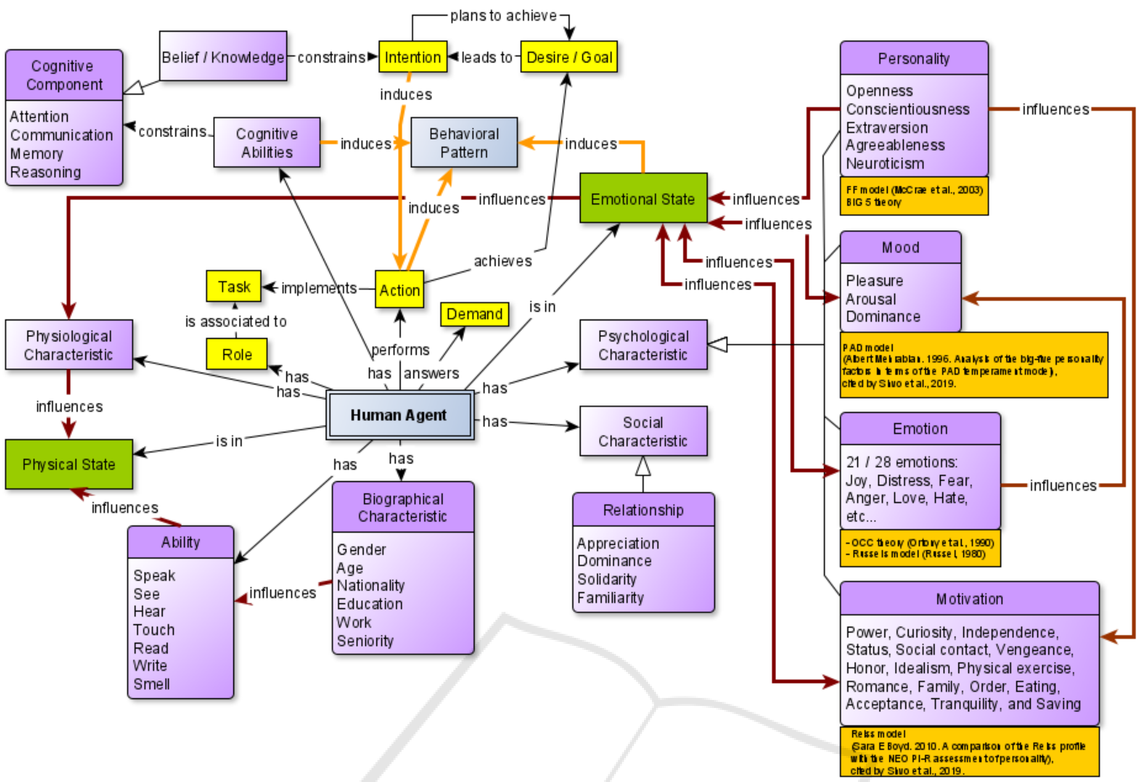

Figure 2: Preliminary human model for HDT.

5 DISCUSSION

The first interest of the HDT in industry is probably to emulate human worker behaviors and interactions with its surrounding, knowing this behaviour. From the production perspective, it would ensure humans can be integrated in predictive maintenance processes like it is done now with machines and undesirable events caused by human behaviour can be anticipated for dynamic adaptation of the shop floor. From the human perspective, it would ensure well-being and quality of experience, with tasks tailored to workers. In this context, the HDT is a step towards resilience of industrial settings. Of course, this needs to be understood as a coarse illustration of the fact that HDT can allow to maintain human's well-being over long-term and to anticipate any kind of deterioration of his conditions - physical as well as psychological.

But the most interesting comes when considering the perspective it opens for control and supervision with collaborative decision-making among DTs. HDTs could share their knowledge of the human model and internal state with the non-human DTs, so that they can integrate it in their own reasoning. This leads to environments where collaborative decision-making can be implemented, all DTs interacting together in the back to dynamically optimise the overall objective by adapting machine commands and sending warnings, instructions or recommendations to human workers. DTs and HDTs would then act together as a system of autonomous agents, at any time respecting the constraints and preferences of their respective twins, and trying to reach their own individual objective(s) while acting together to fulfill a common objective.

We have shown in this paper that the HDT is a very young concept that can have a number of functions in different domains, including supporting health and medicine, being the keeper of personal data, the embodiment of our digital shadow, or the digital agent representing a human worker in industry. It can be even much more. If the focus here was industry, the necessity to have a proper human model is domain-independent. Here we have highlighted the important factors to investigate and the relevant theories and existing models, constituting a basis for building a future model formalising not only the structure but also the behaviour. For each of the variables, the dedicated theories and models need now to be carefully integrated. The model can then be progressively refined and assessed on field, until it be-comes precise enough. The challenge will be in particular to model properly the complex influences driving the internal forces.

When the model has reached an acceptable level of accuracy, it can be further implemented as a software agent integrated in a DT structure, to simulate a human worker, learning and adapting from the worker behaviour and synchronising with the field, to reach a state where emulation is possible. Of course the HDT by nature carries all the concerns linked to data protection, acceptance and ethics, which we did not address here. This is another story...

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