A NEW MODELING FRAMEWORK FOR CYBER-PHYSICAL AND HUMAN SYSTEMS

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ABSTRACT

Health, manufacturing, and transport systems are in the midst of the rapid emergence of intelligent systems. In this regard, Cyber-Physical and Human Systems open a new window on intelligent systems in which the role of humans is prominent. Modeling and simulation (M&S) are recognized as practical tools playing a role in promoting the design, analysis, and development of CPHS. However, from a conceptual and technical point of view, CPHS modeling is challenging for modelers since they face some concepts and processes regarding human beings and intelligent artifacts which were not pervasive in M&S before. Thus, the aim of this study is twofold. The first is to shine new lights on the CPHS understanding regardless of application domains by providing an ontological model. The next is to propose an agent-based modeling framework according to the High-Level Language for Systems Specification (HiLLS) to convert conceptual models into executable ones.

Keywords: Cyber-Physical and Human Systems, High-Level Language for Systems Specification, Ontology, Meta-model, Agent-Based Modelling.

1. INTRODUCTION

Due to revolutionary advances in communications and computing technologies, Cyber-Physical Systems (CPS) have emerged to bring interactions between cyber and physical components through a single system. In recent years, many investigations have been carried out on CPS. As we explore CPSs, we face the growing role of humans in such systems. Cyber-Physical and Human Systems (CPHS) is maturing relatively new area paying particular attention to human beings and ties them with CPS (as a whole) and its components in an intertwined way. In such a manner, we are witnessing a shift from classic CPSs to CPHSs and shaping more sophisticated and human-friendly systems. The application of CPHS is wide-ranging (e.g., smart homes, intelligent manufacturing systems, robotic surgery, and smart grids). These systems play an essential role in the new vision of a human-centered society in Japan (Society 5.0) and the future industrial revolution in Europe (Industry 5.0) by using different technology classes such as IoT, edge and cloud computing, virtual and augmented reality, wearable and tactile sensors, digital assistants, and collaborative robots.

Although considering humans as a pivotal part of CPSs brings new opportunities and advantages, it provokes additional challenges in the design, implementation, and development. These challenges may be rooted in the unpredictability, complexity, and still not fully understood nature of human beings, such as interests, cognition, and behavior.

Modeling is recognized as an effective tool for promoting the design, analysis, and development of CPHS. Understanding humans' behavioral, psychological, and physiological aspects, as well as systemic mechanisms and technical challenges, are among tremendous obstacles for engineers to model human-centered systems. In this line, modelers are often interested in a framework to give them an overview of CPHS and provide them with structures and methods to build a CPHS model irrespective of the application field. Some attempts in literature have been undertaken to consider humans in CPS. However, they did not provide a systematic approach to building simulation models for CPHS. Moreover, often only ad-hoc solutions are presented. In addition, some characteristics that impact humans' structural and behavioral complexities (such as emotion and interest) bring CPHS some unprecedented challenges that have not yet been addressed in modeling.

In this paper, we present an ontological framework to explore CPHS from the standpoint of system theory. This conceptual model contains a concept map that describes CPHS regardless of the application domain and determines the elements and modellable operations of the system. Then, we propose a meta-model that allows modelers to derive an executable simulation model from a conceptual one. The rest of the paper has been organized in the following manner. Section 2 looks at the background of CPHS and reviews the literature on M&S efforts. The CPHS ontological structure is discussed in the next section. We dedicate section 4 to the meta-model for simulation. Section 5 will present an illustrative case, and the last section draws upon the conclusion and gives some perspectives for further research.

2. BACKGROUND AND LITERATURE REVIEW

CPHS has its roots in Cyber-Physical Systems (CPS). Lee (2015) defines CPS as an orchestration of computers and physical systems such that embedded cyber parts monitor and control physical processes. Although the first application of the term CPS pertained to the embedded system, it progressively received a broader sense (Um 2019). Nowadays, CPS points at three system scales. It may refer to a small-scale system (embedded CPS), e.g., a mini-robot, a complex and large-scale system such as an autonomous car, or a very large-scale system like a smart city. In general, small-scale systems engage humans in design (Koreshoff, Leong, and Robertson 2013). Then their components follow the physics laws. Large and very large scale CPSs have mostly decentralized forms reflecting event-oriented and discrete systems. In large and very large CPSs, humans get involved in different phases (e.g., design, testing, operating, and use) and may play roles in and out of the loop (Horváth 2014). The human-inside-the-loop refers to situations in which CPS needs human intervention to be operational (e.g., ATMs). The human is placed outside the loop when CPS operates independently, but human inputs should activate the system (Wang and Wang 2018).

It did not take long to be recognized that understanding human characteristics (including emotions, needs, intentions, and learning) is crucial for the improvement and efficiency of CPSs (Nunes, Silva, and Boavida 2018; Mukhopadhyay et al. 2020). Since compared to machines, human actions and behaviors are exposed to several environmental, natural and personal factors, the efficiency of CPSs requires much more effort (Yilma, Panetto, and Naudet 2021). In this regard, more attention was paid to the interrelation of human beings and CPS, resulting in a new concept that enlarged CPS's scope to include human requirements.

CPHS (also called Cyber-Physical-Social System) is a name that has come into use to describe the arrangement of human, cyber and physical parts to perform tasks and achieve specific goals (Zhou et al. 2019; Nunes, Silva, and Boavida 2018; Sowe et al. 2016; Krugh and Mears 2018). Zeng et al. (2020) believe that the primary purpose of CPHS is to provide services for users. In other words, CPHS is a CPS closely combined, organized, and integrated with the characteristics of humans (Wang 2010; Wang et al. 2019).

Despite the undeniable usefulness of M&S to design, develop, and improve complex systems, limited efforts have been undertaken to apply it to CPHS. Some scholars tried to provide descriptive and interpretive models and frameworks for CPHS. Carreras Guzman and colleagues (Carreras Guzman et al. 2020) posit that CPHS should be considered a specific socio-technical system. In this respect, Brauner and Ziefle (2019) studied CPHS from a socio-technical perspective (comprising the structure, humans, task, and physical components) and explored the human decision-making process. Smirnov et al. (2014) suggested an upper-level ontology for CPHS. Their work focuses on two kinds of resources and makes an attempt to show the self-organization of CPHS resources; however, they ignored the CPHS's process and dynamicity (e.g., learning).

Yin, Ming, and Zhang (2020) used a 5C level structure presented before by Lee (2015) for CPS to propose a seven-layered framework for CPHS. This framework exhibits the integration of cyber, physical, and social space. The weakness of this framework is the failure to study the nested CPHS. Besides, the analyzability of components and purposefulness of the interested system cannot be fully perceivable. Another drawback is that human physical actions have not been considered in the framework.

By stressing human-machine collaboration, Berger et al. (2020) presented a generic model to describe the architecture of a CPHS, which helps designers identify the needs, tasks, and activities of CPHS. They used SRK (Skill-based, Knowledge-based, and Rules-based), DIK (Data, Knowledge, and Information), and AADA (Acquisition, Analysis, Decision, Action) models to describe CPHS tasks. They believe that the generic architecture is a first step to addressing challenges in CPHS. Despite its simplicity and efficacy approach, it suffers from several significant shortcomings, such as social aspects. Yilma, Panetto, and Naudet (2021) reviewed the research conducted on CPHS and depicted a multi-dimensional view of CPHS. They reached a high-level systemic model to demonstrate key systemic concepts for CPHS design. This model used UML 2.0 notation and formalized a CPHS in the context of relation, behavior, function, structure, objective, interface, and environment. Nevertheless, their proposed meta-model did not use the process approach and cannot explain how human characteristics and behaviors impact CPHS.

By using the theory of systems and process approach, our ontological framework gives an overview of CPHS, describes CPHS components, and demonstrates how concepts become interrelated to make the processes operable and make system goals accessible.

All the reviewed studies carry various limitations for modelers because they are limited to a conceptual view of CPHS without providing enough details for simulation. Most investigators have examined M&S in CPS areas in order to evaluate complexities and behaviors. Mittal & Tolk (Mittal and Tolk 2019) treated the complexity of M&S applications for CPS engineering. They deem that CPSs are multi-agent systems, and the CPS models should be thought of as a hybrid systems dealing with both continuous and discrete systems. Intelligence, adaptation, and autonomy aspects have been considered in CPS agents in a broader context. However, no methodology to extract a CPS simulation model is proposed. Hehenberger et al. (Hehenberger et al. 2016) analyzed CPS from different perspectives and asserted that cloud-based systems (e.g., IoT and distributed CPS) require more M&S abstraction levels. They highlighted three concerns regarding the M&S of CPS. The first matter is related to modeling the components from various disciplines. The second one pertains to the modeling of interfaces among components, and the third concerns model integration. While they seek methods and applications for the design, modeling, simulation, and integration of CPS, the lack of development roadmap and shortcoming of social dimension is evident in their work. Weyer et al. (2016) discussed the M&S of intelligent factories and tackled the dynamic design, particularly for virtual commissioning. They provided a reference three-layered framework (i.e., appliers, information interface, and data acquisition). These layers pave the way for the interoperability of CPS models. Similar efforts toward CPS modeling can be found in which the social aspect does not matter. For example, the agent-based cooperating smart objects conducted by Fortino, Russo, and Savaglio (2016), the generic conceptual architecture supporting modeling from the business level to the infrastructure level carried out by Dumitrache et al. (2017), and the CPS Conceptual Model introduced by the CPS Public Working Group (Griffor et al. 2017).

The present work intends to provide an exciting opportunity to fill the gap between the CPHS concept understanding and its simulation model. To do so, we propose an agent-based modeling framework based on High-Level Language for Systems Specification (HiLLS) to convert CPHS conceptual models into executable ones.

3. ONTOLOGICAL MODEL

The ontological framework represents an abstraction of CPHS containing merely concepts to establish a structure delineating the system and revealing a degree of knowledge of its internal processes (Grey-box). CPHS can be perceived as an open or closed system made of a large number of components that have many attributes and interactions and manifest deterministic and non-deterministic behaviors.

3.1 System

Figure 1 gives a systematic view of CPHS. We contend that inputs, structure (interactions), components (at least including one social, cyber, and physical component), outcomes, needs, rules, and processes are essential elements to characterize a CPHS. The structure of CPHS illustrates the potential relationships between components that cause the system's behavior to be different from the behavior of a single component. Due to the changeable connections, the CPHS structure is generally dynamic. However, the interactions may be restricted by specific rules and conventions. These limitations may also be imposed on component roles, mechanism of processes, or the component's interactions. Irrespective of design and purpose, an intelligent system cannot become isolated and requires input to manifest behavior. Accordingly, CPHS interacts with its environment at different levels to exchange Energy, Matter, People, or Information (EMPI). The operations on inputs are organized by way of CPHS processes in which each component takes over specific roles to allow the system to generate the outcome.

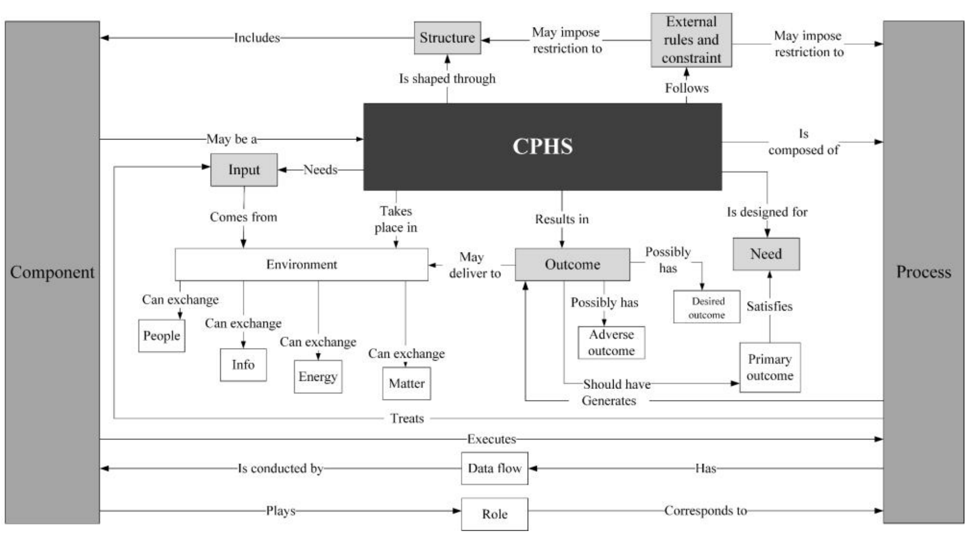

Figure 1: Ontology for CPHS modeling.

3.2 Components

Figure 2. illustrates the concepts related to the CPHS components. Each component has specific characteristics and abilities to play its roles in CPHS processes, as well as a communication mechanism to join the structure and environment through EMPI channels. The CPHS components can be categorized into combinative and non-combinative parts. Non-combinative parts refer to the cyber, physical, and human parts independently involved in CPHS processes. Among non-combinative parts, humans (at the population or individual level) have a particular position because they can have both cyber and physical abilities to realize mental and physical actions that enable them to take over various roles in CPHS (Nunes et al., 2018). For example, they can act as sensors to collect data and information, processors to interpret the data, decision nodes to control the system, and physical operatives to perform physical operations.

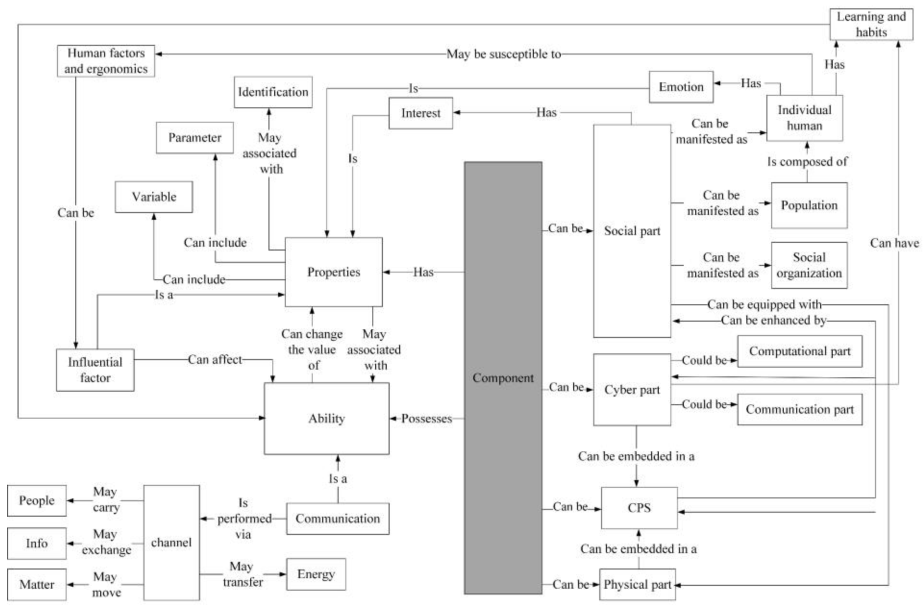

Figure 2: Details of the component entity.

In general, many features can be imagined for human beings; however, certain features are dominant in CPHS. *Interest, emotion, communication, and human learning and habits* are the main concepts of human nature to be remarkable in CPHS. These features can direct or reinforce emotional, goal-oriented, and experienced behaviors.

- *Interest:* People are engaged in processes by interest. (Nunes, Silva, and Boavida 2018) underline that interest is a crucial research challenge in CPHS because humans without personal interest do not tend to act in favor of the system.
- *Emotion*: The impact of emotions on human behavior and cognitive and physical abilities is not deniable (Dolan 2002). In a broad sense, emotions can be either primary, which determines instinctual behavior, or secondary, which influence cognitive processes, e.g., information perception, commitment, and speed of decision making (Pfister and Böhm 2008).
- *Learning and habits:* Human learning refers to acquiring experience leading to a permanent change in behavior or in behavior potentiality (Olson 2015). Humans profit from different kinds of learning. Behaviorism (learning by stimuli and responses), social learning (learning by observation), and cognitivism (learning by mental phenomena and reasoning) are prominent human learning theories (Ormrod 2016). Learning and habits have mostly the same principles and mechanisms but different interpretations. Learning aims to gain new knowledge and, consequently, novel behaviors, while habits tend to obtain information to keep and reinforce the current behavior.

- *Communication:* Human communication is not just the exchange of simple messages but also context-dependent (Bhattarai 2012). Thus, interpretation is often required to find meaning within a particular situation and context.

The combinative component refers to a set of non-combinative parts that operate as a unit within the processes. For example, integrating cyber and physical parts builds CPS. The combination of CPS and an individual leads to the emergence of augmented humans, and augmented cognition emerges in the case of equipping humans with cyber components.

3.3 Processes

Perception, decision making, and physical operation are three core processes in CPHS. The components take on the roles in one or a set of processes to shape the system's behavior. Figure 3. shows the concepts of the CPHS process (Rectangles) and the potential roles of components (Ovals).

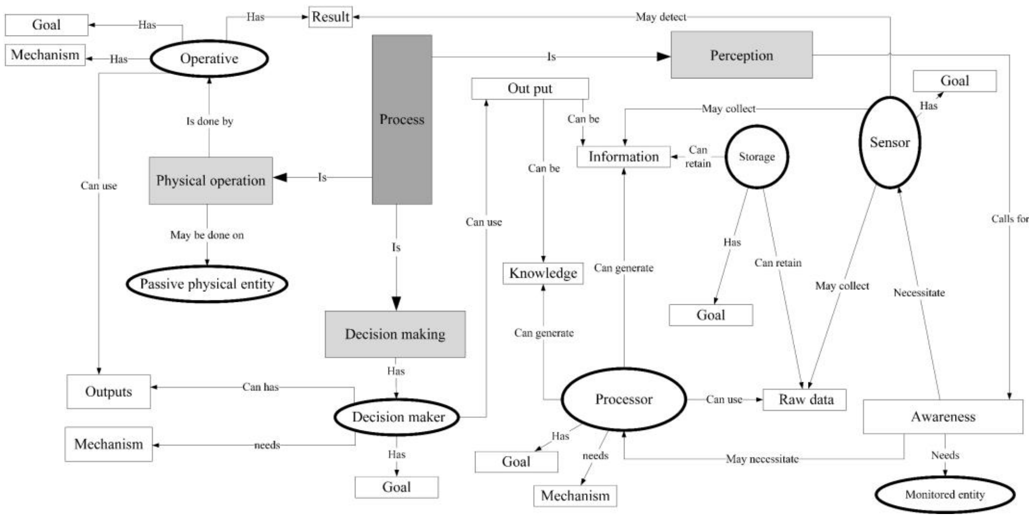

Figure 3: Details of the process entity.

Smirnov et al. (2014) state that intelligent systems are all context-aware systems. This is why being aware of the situation of entities is one of the most critical features within CPHS (Noor and Minhas 2014). The perception process gathers and provides data, information, or knowledge to determine the component's attributes and current or future status. Thus, the main objective of this process is to obtain awareness, whether through sensors (to collect raw data) or processors (to obtain information and knowledge). Sahinel et al. (2019) underline that human beings should be considered part of perception when the system needs to understand human behavior and react to this behavior.

Decision-making refers to choosing between alternative solutions to regulate or initiate physical operations in the system. Decision-making can cope with situations in which awareness is deterministic, probabilistic, or deficient. For example, when humans act as decision-makers, they can make irrational, perplexing, or emotional decisions ignoring available awareness. This may be rooted in the fact that human preferences and cognition are primarily unknown and hard to measure.

A physical operation can encompass predictable or unpredictable behavior executed by physical systems that consume energy. Decision-making process events cause predictable physical behaviors in the physical world. Nevertheless, conscious decisions may not always precede physical behavior. Unpredictable physical behaviors are those influenced by stimuli that the system is unaware of and result in events in physical space (e.g., sudden breakdowns that lead to changes in the behavior of physical equipment.). It should be noted that humans can contribute to physical operations through both predictable (commitment) and unpredictable (free will) ways.

4. META MODEL FOR MODELLING AND SIMULATION

To understand the mechanisms governing the behavior of a complex system, we must be able to measure its state variables and model the dynamics of each of the system's components. Here, we develop an agent-based conceptual model for simulation. Typically, discrete-event models are utilized as the most intuitive models to grasp all forms of dynamic models (Zeigler, Muzy, and Kofman 2018). An event is defined as an instantaneous incident that can move the current state of the agent to a new state (Carson 2005). High-Level Language for Systems Specification (HiLLS) is a high-level language composed of concepts from system theory and software engineering using concrete notations to spell out the structure and behavior of agents. This graphical language federates Unified Modeling Language (UML), Discrete Event system specifications (DEVS), and Formal Methods (FM) to promote Model-Driven Engineering (MDE) techniques with the purpose of complex systems modeling (Samuel, Maiga, and Traoré 2019). HiLLS allow modelers to define agents as H-Entity, i.e., H-System and H-Class agent (Aliyu, Maïga, and Traoré 2016). Hentities can be linked together by the UML notations, i.e., inheritance and composition relations. This enables modelers to divide the complex model into several smaller and less complex models that are as independent as possible. H-System contains variables, operations, and Phase Transition Diagram (PTD). A phase is defined as a set of states that meet some conditions (Samuel, Maiga, and Traoré 2019). Phases are classified into finite ($T = t$), infinite ($T = \infty$) and transition ($T = 0$) phases. The behavior of the H-System is demonstrated by PTD, and the transitions between phases follow the rules of DEVS. However, the main difference is that, unlike DEVS, coupling and atomic models in HiLLS can be represented in the same way. Two boxes at the left and the right denote input and output ports to exchange agents (Hentities) or information with its environment. The communication capability provides the foundation for cooperation among agents to achieve common goals.

Communications in HiLLS are defined in two ways to support simulation: (1) Direct communication is made by messaging called Events (Aliyu, Maïga, and Traoré 2016). Therefore, direct communication is dedicated exclusively to H-System agents who have the ports to exchange messages with others. (2) Indirect communication allows access to information that other agents make public. This mechanism uses the methods of agents to read the value of public variables of other agents.

An agent-based architecture forms the CPHS model in which a central H-system controls the CPHS structure, determines data flow, and defines the roles of components in order to generate primary outcomes. CPHS H-System has indirect communication links to all CPHS components in order to read the value of public attributes without messaging. In this network, the components are manifested as H-Entities that include abilities, properties, communication mechanisms, and behaviors to execute processes. When a component is involved in a complex process (e.g., multi-mode physical operation) or has a sophisticated ability (e.g., learning) to perform a process, its behaviors can be developed as a separate agent (sub-process). All CPHS components are modellable through passive, active, and learner agents (See Table 1).

Table 1. A comparative view of agents' features.

Feature	**Description**	**Passive agent**	**Active agent**	**Learner agent**
Operational independence	*Agent can be developed and executed independently.*	+	+	+
Extensibility	*Agent can have sub-process.*	+	+	+
Evolutionary behavior	*Agent has learner sub-process.*	-	-	+
Exhibit behavior	*Agent has PDT and can change its behavior.*	-	+	+
Connectivity	*Agent can exchange massage with others.*	-	+	+

Passive agents have no behavior. In comparison, active and learner agents can manifest various behavior. Learner agent possesses brain sub-process that provides learning capacities for its process(es) by converting the novel information into knowledge. The brain allows the learner agent to have evolutionary behavior over time. As Adelani (2014) discussed, Artificial Neural Network (ANN) is a general mechanism that can be exhibited by HiLLS and applied quickly to a wide range of cases. Therefore, it seems that ANN is ideal for modeling this H-Class brain agent. In the CPHS agent-based architecture, an H-system called frame is responsible for determining the conditions and behaviors under which the system is modeled (rules, needs, outcomes, and interaction with the environment).

Figure 4. shows the proposed HiLLS meta-model for CPHS. This modular and extensible structure can be implemented through various programming languages.

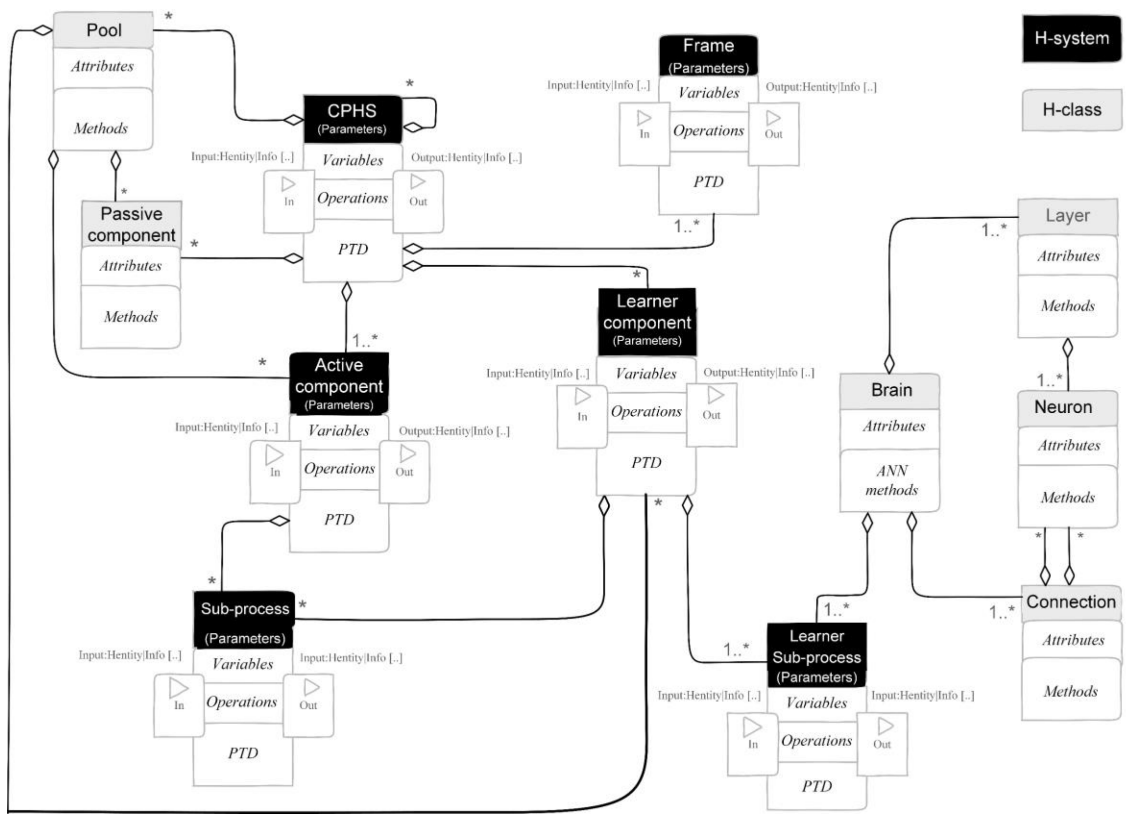

Figure 4: HiLLS-based CPHS meta-model.

Samuel et al. (2020) proposed a verification and validation (V&V) framework for HILLS to check both the system of interest and the requirements. We use the same approach for the V&V of CPHS.

5. ILLUSTRATIVE CASE

An elder with chronic diabetes and movement disorder lives alone in a smart house. He has an implanted sensor to monitor his blood sugar, heart rate, and blood pressure. In his living room, a healthcare appliance is responsible for collecting and analyzing all sensor data and sharing information with his doctor, family members, social robot, and emergency staff when needed. A mobile social robot assists the senior in cognitive (e.g., reminding doctor appointments) and physical tasks (i.e., lifted, opened, rolled, moved, turn, and tipped the objects). To find the right path to the selected object, the robot is able to detect its surrounding physical entities (e.g., pot and table) situated in a range of two meters. This robot works continuously until the battery falls below a defined threshold, then goes to its charging port. After the complete charging cycle, the robot will be ready to work. This robot can detect the person's six facial emotions of happiness, sadness, fear, anger, surprise, and disgust and five types of voice tone, i.e., directive, assertive, friendly, questioning, and conversational. Social robots learn from their environment, particularly from their users. The acquired knowledge from the learning leads to better coordinating their behaviors with the user. It means that the robot observes the person's behavior and learns repetitive and imitable ones. When such behavior occurs, the robot can anticipate and act on needs. For example, the senior would like to turn his chair to the window and watch the garden. When this behavior occurs for the first time, the social robot should approach the chair to identify its features, e.g., geometrical shapes, bright and distinct colors). With the repetition of this behavior by the senior, the social robot learns when and in what circumstances (e.g., when he is healthy, not angry, has no appointments, and uses a friendly tone) to carry out a proactive action and turn the chair before the senior action. The senior, healthcare appliance, social robot, and chair are the four main CPHS components. We can also imagine the table and pot as two subsidiary parts. As previously mentioned, each component can play one or more roles to run CPHS processes. Table 2 presents the conceptual roles and modeling methods of components.

Table 2: Components' roles and agents' models

Components	**Type**	**Roles**			**Agent type**	**CPHS agent**
		Perception	**Decision making**	**Physical operation**		
Senior	Combinative	Monitored entity	Decision maker	Operative	H-System	Active component
Healthcare appliance	Non-combinative	Processor	Decision maker	-	H-System	Active component
Social robot	Combinative	Sensor	Decision maker	Operative	H-System	Learner component
Chair	Non-combinative	Monitored entity	-	Passive entity	H-Class	Passive component
Table	Non-combinative	Monitored entity	-	-	H-Class	Passive component
Pot	Non-combinative	Monitored entity	-	-	H-Class	Passive component

Since the cause of senior behavior is unknown for the system, at first, his physical action is considered as unpredictable behavior. We deem that the values of blood sugar, blood pressure and heart-rate follow a normal distribution. To keep this example simple, the healthcare is set to use thresholds to monitor health indicators and share information with interested parties. The social robot contributes to the all three processes with learning capability. In this regard and to be more apparent, we develop three subsystems to model its physical, decision-making process and learning states.

The characteristics of the passive objects are essential for senior and robot perception. The awareness agent is developed to make information available regarding physical entities to provide perception for the elderly and the robot. Figure 5 depicts the smart home model. PDTs have been developed based on the syntax of HiLLS' phases and transitions provided by Aliyu, Maïga, and Traoré (2016).

6. CONCLUSION AND PERSPECTIVES

CPHS will have definitely a fundamental role in the coming industry 5.0 and society 5.0 paradigms. M&S provides a way to grasp the behavior of the CPHS without doing physical experiments. For such a reason, we first provided an ontology describing CPHS and its main components. Then, in view of the ontology, we presented an agent model structure based on HiLLS that can be served as a guide for the design and development of simulation models. Thus, the presented methodology is best supported by systematic conceptualization and modeling mechanism. There is still a lack of research on real-time simulation of CPHS and also validation methods for human behavioral models in CPHS as a socio-technical system. We hope that our interest in the topic becomes contagious and opens new doors for researchers to develop better CPHS models.

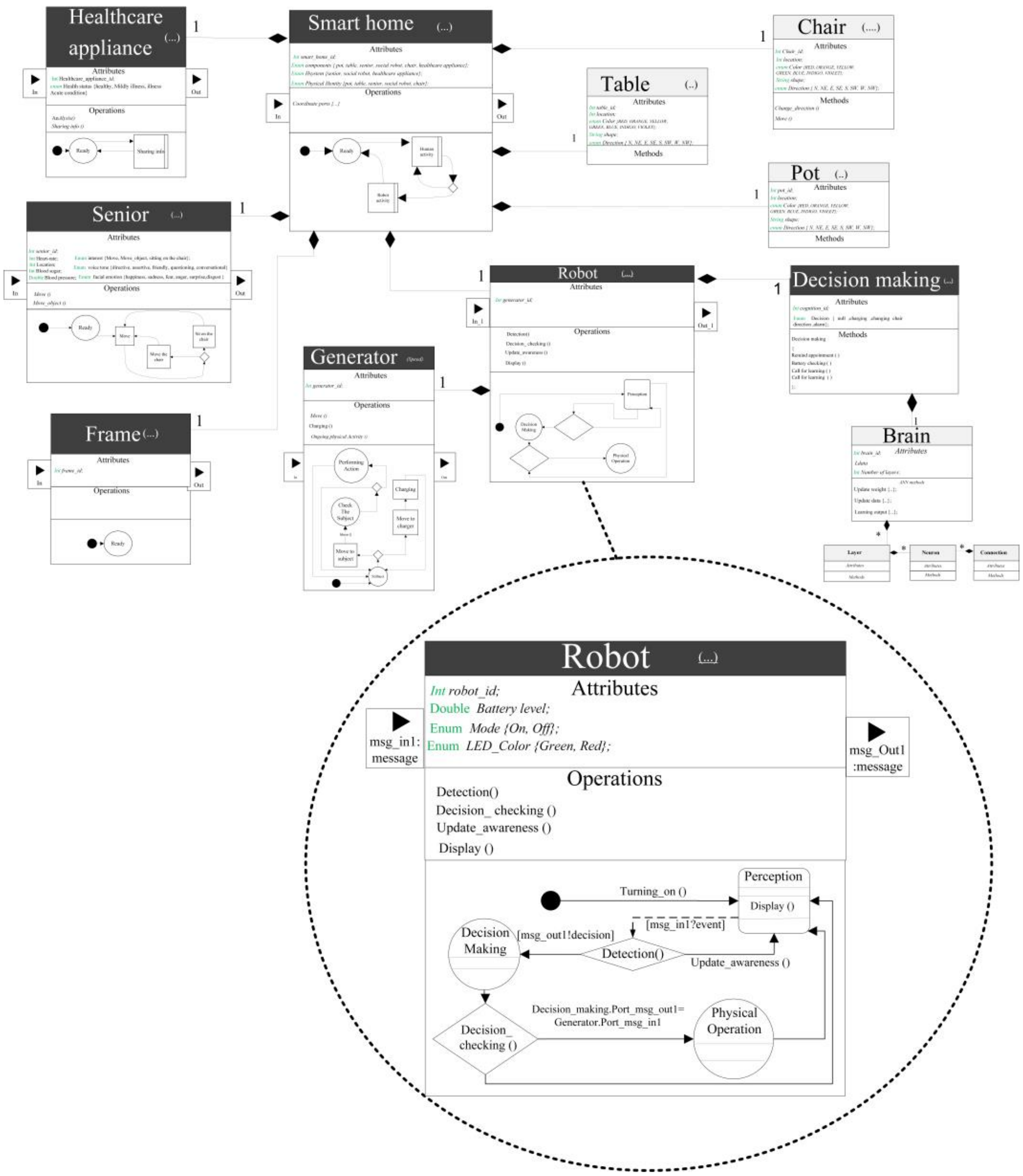

Figure 5: HiLLS-based smart house model

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