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# A framework for AI-based self-adaptive cyber-physical process systems

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**Abstract :** Digital transformation is both an opportunity and a challenge. To take advantage of this opportunity for humans and the environment, the transformation process must be understood as a design process that affects almost all areas of life. In this paper, we investigate AI-Based Self-Adaptive Cyber-Physical Process Systems (AI-CPPS) as an extension of the traditional CPS view. As contribution, we present a framework that addresses challenges that arise from recent literature. The aim of the AI-CPPS framework is to enable an adaptive integration of IoT environments with higher-level process-oriented systems. In addition, the framework integrates humans as actors into the system, which is often neglected by recent related approaches. The framework consists of three layers, i.e., processes, semantic modeling, and systems and actors, and we describe for each layer challenges and solution outlines for application. We also address the requirement to enable the integration of new networked devices under the premise of a targeted process that is optimally designed for humans, while profitably integrating AI and IoT. It is expected that AI-CPPS can contribute significantly to increasing sustainability and quality of life and offer solutions to pressing problems such as environmental protection, mobility, or demographic change. Thus, it is all the more important that the systems themselves do not become a driver of resource consumption.

**Keywords:** artificial intelligence; business process management; cyber-physical-systems; framework; Green AI; process-aware information system.

**ACM CCS:** Computer systems organization → Embedded and cyber-physical systems.

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# 1 Introduction

The networking of mechanical and electronic components with their virtual representation through a corresponding data infrastructure, generally found in a *Cyber-Physical System* (*CPS*) [1], is a current megatrend in science and industry [2]. The vision is the connection of isolated embedded systems into a common network, creating distributed, highly complex systems that can dynamically adapt and optimize each other. This development is driven in particular by the ongoing progress in *Information and Communications Technology* (*ICT*) and the trend towards the *Internet of Things* (*IoT*) [3]. One of the most important application scenarios of CPSs are *Process-Aware Information Systems* (*PAISs*) [4] and specifically *Workflow Management Systems* (*WfMSs*), since they are ubiquitous in companies across all sectors.

Integrating functionality of CPSs into WfMSs poses several challenges (cf. [5, 6]) that are mainly caused by missing connectivity and communication abilities, as well as by isolated and not interoperable systems [7–9]. That is, high-level applications such as WfMSs only rarely have access to or beneficially use information provided by low-level IoT devices such as sensors or actuators. Research on this problem of integrating CPS components into a larger process context is still in its infancy [7–10]. At the same time, humans play a crucial role in CPSs, on the one hand as individuals interacting with physical actuators, and on the other hand as central decision-makers with specialized knowledge. In addition, *Artificial Intelligence* (*AI*) methods that are inevitably required for reaching these goals are only used to a limited extent. Current research with proper consideration of these aspects is still in its infancy, reducing the applicability of many methods in real-world scenarios.

We aim at addressing these issues by discussing a framework for realizing CPSs in such a way that they enable resource-efficient and adaptive processes involving a wide range of IoT devices as well as human actors in complex application scenarios. We refer to such systems as *AI-Based Self-Adaptive Cyber-Physical Process Systems* (*AI-CPPS*), since the focus here is on the integration of *Business Process Management* (*BPM*) with AI methods as an extension of the traditional CPS view. AI as an enabler in CPSs has the potential to address the large heterogeneity and dynamic complexity in such systems [11]. AI-CPPS thus become self-learning and resilient by reacting intelligently to unexpected situations and continuously improve in terms of their benefits for humans as well as their sustainable operation.

The main contribution of this paper is a generic framework for AI-CPPS that can be adopted to systematically and predictably design implementations for different application areas. Typical application scenarios in which AI-CPPSs can be used are found in heterogeneous, knowledge- and planning-intensive (work) processes from areas such as robotics [12], resilient supply chains and production [10, 13–16], services [11], smart cities [17], intelligent logistics systems [18], and various other domains. The framework is structured into three layers dealing with processes, semantic modeling, as well as systems and human actors, along which we discuss challenges and respective solution outlines. The remainder of this paper is structured as follows: Section 2 describes the AI-CPPS framework in more detail, with layer-specific challenges and the corresponding solution outlines. The application of the generic approach is discussed for, and demonstrated on, two selected application scenarios in Section 3. Finally, Section 4 summarizes the paper and concludes with an outlook of future research directions.

# 2 Framework for AI-based self-adaptive cyber-physical process systems

In this section, we present the framework for AI-CPPSs. As already mentioned, AI-CPPSs aim to integrate AI methods with BPM and provide the basis for more efficient, robust, and resilient processes in cyber-physical environments (cf. [13, 14, 16]). Compared to related approaches, we present a generic framework for developing AI-CPPS in this paper. In addition, we introduce application scenarios in which this generic framework can be used and describe what is needed for application. In contrast to other related approaches, the focus of the AI-CPPS framework is to integrate humans as an actor into the framework. In the following, we present a generic framework and *General Challenges* (*GC*) for applying the model. Subsequently, we discuss concrete challenges for each layer in Sections 2.1–2.3.

In Figure 1, the proposed framework with several layers for an AI-CPPS is illustrated. It consists of three layers: (A) the process layer on top, which entails the simulation, execution, and analysis of processes which are monitored, controlled, or otherwise adapted by advanced AI methods within the AI-CPPS framework, (B) the semantic modeling and integration layer, which links the processes to the underlying systems by designing a semantic description to integrate the components, and (C) the cyber-physical systems and human actors layer, which focuses on the systems and ways humans interact with them as well as how human actors should be represented in the processes. In this way,

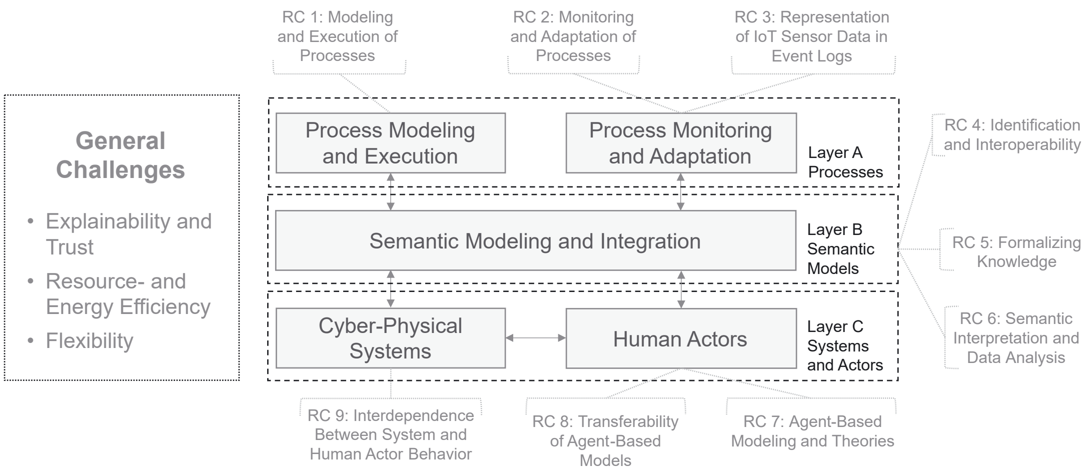


**Figure 1:** Framework for AI-based self-adaptive cyber-physical process systems.

the proposed framework provides a generic approach that can be implemented with any communication standard and physical component or actor. In addition, we identify general challenges from the literature that should be addressed by each layer in the following.

## 2.1 General challenges

**GC 1 Explainability and Trust** in processes represent a key challenge for the successful development and use of AI-CPPS. A major driver of AI-based systems is Machine Learning (ML), which is often based on statistical and massively parallel algorithms. This forms a correlation as a foundation for process design, which is not necessarily based on causal relationships. In addition, the complexity of such approaches is very high and the resulting processes and sub-processes are difficult to understand by humans. In order to improve the explainability of systems and especially their behavior, semantic representations and symbolic inference are often proposed in current research to complement classical ML approaches [19]. Such approaches usually increase transparency about the origin of data, its interrelationship, and the parties involved in process design and execution.

**GC 2 Resource- and Energy Efficiency of Software and ICT Systems** is a rising focus area, especially with data-driven and AI-based systems. The demand for compute- and data transfer resources, as well as software-induced obsolescence of hardware, require AI-CPPS (as well as all other software) to take their resource- and energy efficiency into account [20]. To achieve this, both the stakeholders and the system landscape need to be included in the process of assessing, interpreting, and optimizing the energy- and resource efficiency along the life-cycle of the systems. For AI-CPPS, the heterogeneity of the systems, the transfer of the AI components from centralized to distributed Edge-AI [21], and dynamically generated data from running process instances are important challenges when trying to assess the resource- and energy efficiency. While the hardware design in edge systems is already very resource- and energy efficient, the decentralization of the AI algorithms may have positive influences on the resource consumption. However, restrictions in the hardware, e.g., lower compute power, limit the viable implementations. The modeling and engineering of adaptive soft- and hardware for AI-CPPS therefore requires innovative approaches that take this limitation into account and ensure efficient development and execution.

**GC 3 Flexibility** is the main argument in favor of distributed autonomous systems at present. This means that in the event of a failure of system components (e.g., failure of a service provider), other parts of the system automatically realize allocation of resources to match the demand in consultation with the other participants [22]. This also affects processes that are executed in smart environments. Since the focus of AI-CPPS is on processes, the flexibility of processes during their execution should be enhanced. For this purpose, advanced AI methods can be used to enable more flexibility that is typically not given during execution in standard WfMSs.

In the following, we address the layers of the framework in detail, discuss individual research challenges for each layer, and introduce possible solution outlines that can be applied to better address the challenges. In Section 3, we then present application scenarios in which AI-CPPSs can be beneficially applied, and corresponding research artifacts be created.

## 2.2 Modeling, execution, monitoring, and adaptation of cyber-physical processes

### 2.2.1 Problem statement

Recently, BPM [23] gained importance and high interest in various applications domains, e.g., in companies and daily businesses, in public administrations, as well as in smart environments (e.g., [8, 9, 16, 24, 25]). The application of BPM in cyber-physical environments is particularly promising, as the low-level IoT devices provide crucial information regarding the discovery and analysis as well as the execution and monitoring of processes. However, to benefit from a stronger coupling, several challenges must be addressed [5, 6, 9]. These challenges affect several phases of the BPM lifecycle [23]: During *Process Discovery*, IoT sensor data can be used to enhance the quality of resulting process models mined from data. In addition, the data generated can be utilized for *Process Analysis*, *Process Redesign*, and *Process Monitoring*. However, the processing and use of IoT sensor data that is generated during process execution and which should be used for analyses, optimizations, and improvements (cf. *Process Mining* [26]) is difficult, since IoT sensor data is currently not combined with process data in event logs. During *Process Redesign*, a further issue needs to be addressed: the automatic adaptation of processes, as the companies are faced with processes that are not modeled in sufficient detail and lack the necessary flexibility during execution to react quickly to exceptional situations. For this purpose, enhanced flexibility is required. However, current WfMSs do not offer the necessary (automatic) mechanisms to adapt processes appropriately in the case of previously unknown situations [4]. This poses a big problem in BPM, namely the error-prone and time-consuming redesign of processes that is primarily performed manually by domain experts [5].

### 2.2.2 Research challenges

In order to benefit from more efficient, robust and, thus, more resilient cyber-physical processes, a stronger coupling between higher-level systems such as *Enterprise Resource Planning (ERP)* systems, *Manufacturing Execution Systems* (*MESs*), or WfMSs is required [8, 9, 24]. In the following, we present a non-exclusive set of research challenges that should be addressed to pave the way for IoT-based BPM and, thus, to achieve the mentioned advantages. The research challenges are based on existing literature (cf. [6]) and on experiences with our physical smart factory (cf. [8–10, 13, 14, 24]) used for process-oriented research.

**RC 1** *Modeling and Execution of IoT-Based Cyber-Physical Processes*: To execute cyber-physical processes in smart environments, it must be specified which activities are executed in these processes and which resources should be used to actuate them. Typically, this specification is created manually by a domain expert using an appropriate representation language. A challenge in this context is that this modeling task is very time-consuming and requires specific expert knowledge. In addition, there are many different languages that can be used to represent IoT-devices in processes (see [27–29] for comprehensive overviews), and it is difficult to decide which one is best-suited for the current scenario. The choice of a modeling language has a strong impact on the process execution and, thus, the used execution engine.

**RC 2** *Monitoring and Adaptation of IoT-Based Cyber-Physical Processes*: During the execution, the process state must be continuously monitored to enable real-time control, to react to exceptional situations [10, 14, 15], or to optimize the process, e.g., for efficiency. Due to the high volume, velocity, and variety of IoT sensor data, it is a crucial challenge to monitor processes in near real-time and to react to situations immediately. The two main steps for enabling this, namely the definition of patterns that should be identified in IoT sensor data and the adaptation of processes that failed during execution, are currently mostly performed manually by domain experts. Consequently, both tasks are laborious, even for domain experts, and pose certain challenges, especially in highly dynamic smart environments.

**RC 3** *Representation of IoT Sensor Data in Event Logs*: To perform process analyses and optimizations, process event logs should be analyzed to identify and calculate relevant process performance indicators (cf. [30]), e.g., the cycle times of process activities or the utilization of process participants such as resources. In this context, the high volume and variety of IoT sensor data enables a more precise and real-time analysis of process executions directly in the WfMS. Recently and without using IoT sensor data, only small amounts of data are available in the WfMS to calculate environment-related indicators. One major challenge in this context is the representation of IoT sensor data in process event logs, enabling to calculate such relevant and more precise indicators in the WfMS directly or in other related systems such as in process mining tools, i.e., Celonis Execution Management System, IBM Process Mining, Fluxicon Disco. Currently, process event logs are represented by using the *eXtensible Event Stream (XES)* format [31]. However, this standard has not been designed to represent IoT sensor data besides process data. Consequently, the mentioned tools for process mining and WfMSs cannot use IoT sensor data besides process data to calculate indicators or to perform process analysis [32, 33]. In addition, XES has not been intended to integrate knowledge that is correlated to the event data, which is however a major problem in BPM [5].

#### 2.2.3 Solution outlines

In this section, we present solutions to face the previously discussed research challenges. The solutions outline ideas on how to deal with the discussed challenges and also partially address the general challenges presented at the beginning of Sect. 2.

**RC 1: Modeling and Execution of IoT-Based Cyber-Physical Processes** Modeling processes for cyber-physical environments and executing them are difficult challenges. However, the process of modeling processes can be supported by AI methods (cf. [10, 13–15]). We propose to apply *Case-Based Reasoning (CBR)* as a workflow modeling assistance [34] to utilize knowledge from previously created processes for the current modeling phase. The main benefit of using CBR is that previously captured knowledge can be applied in similar situations, enhancing explainability, trust, and confidence in automatically created process models. However, CBR as a knowledge-intensive method is incapable of solving each task by using cases [13, 14]. For this reason, integrating CBR with other AI methods to a hybrid AI approach is promising. For example [13, 14], present the combination of knowledge-intensive CBR with search-intensive automated planning for adaptation of cyber-physical processes. This combined approach can also be used to support users during the creation of process models from scratch.

**RC 2: Monitoring and Adaptation of IoT-Based Cyber-Physical Processes** WfMSs execute processes based on a process model which is typically static, i.e., without the possibility to react to failures apart from those explicitly defined in the model. Since this is insufficient for cyber-physical processes, where problems are too manifold to be fully covered in a process model in advance, a solution is needed to enable process monitoring and failure recovery of unexpected situations during process execution [15]. The MAPE-K control loop [35] is designed for this purpose and proposes a loop consisting of four phases, i.e., monitor, analyze, plan, and execute, to detect and handle exceptional situations during process execution [10, 36–38]. In these control loops, a process is monitored during the execution in the cyber-physical environment. If a failure occurs, the currently executed process as well as the environment are analyzed to create a change request based on the observed symptoms. This request is further refined and transformed into a concrete change plan to adapt the currently executed process in order to solve the detected problem. Finally, the change plan is applied to the process and execution is continued. While MAPE-K control loops provide a blueprint for process monitoring and adaptation, there are still issues with the implementation of these principles in current WfMSs (cf. [10, 38]). This is because standard WfMSs typically neither allow gathering and analyzing IoT sensor data directly nor executing low-level actuation at the control level [8, 9, 24]. Asset administration shells implemented as service-based architectures [24, 37, 39] can encapsulate from low-level commands at the control level and can be utilized with current representation languages such as BPMN 2.0[1] to overcome these issues. In addition to this, *Complex Event Processing* (*CEP*) engines can be used to handle the IoT sensor data that is created during process execution [10, 38].

**RC 3: Representation of IoT Sensor Data in Event Logs** Current standard formats such as XES that are used for representing process event logs have not been designed to represent IoT sensor data besides process data, and this aspect is only rarely investigated in current research. The DataStream representation format [32, 33] can be used as an extension for the established XES standard to allow a joint representation of IoT sensor data in process event logs. The main benefit of this approach is that IoT data can directly be connected to activities in which the data is produced. Thus, it is possible to use this data for analyzing and optimizing processes.

### 2.3 Semantic modeling and integration

#### 2.3.1 Problem statement

Cyber-physical systems are very heterogeneous and made up of different components that generate a lot of different data, which are often stored in isolated data silos. For AI-based planning and monitoring of CPS processes, it is necessary to describe the machine and human actors as well as their data and involved systems in a machine-comprehensible way. The semantic layer therefore focuses on the design of a uniform semantic description that serves the integration of all AI-CPPS components. *Semantic technologies* have their origin in the idea of the Semantic Web, and originally served the purpose of making knowledge from the World Wide Web accessible to computer systems. Particularly noteworthy is the Resource Descriptions

1 https://www.omg.org/spec/BPMN/2.0.2/.

Framework[2] (RDF) and its extension RDF Schema[3] (RDFS), which enable the identification, disambiguation, and linking of information using computers. The capabilities of the Web Ontology Language OWL[4] go beyond this formalization and allow logic-based formalization of concepts. Meanwhile, the use of semantic technologies such as ontologies and knowledge graphs in cyber-physical systems has become established, for example to increase production efficiency or to support predictive maintenance tasks in the Industry 4.0 context [40].

#### 2.3.2 Research challenges

**RC 4** *Unique Identification and Semantic Interoperability of CPS Resources*: Cyber-physical systems consist of a multitude of different actors, components, devices, and services whose relationships to each other need to be defined. The creation of a unique global identification and distinctiveness of all CPS resources is a core requirement for the creation of an interoperable and traceable CPS environment. Therefore, the semantic layer (Layer B) has to provide an integrative approach by describing the different physical actors and resources (Layer C) for the process planning procedures from Layer A in an addressable and identifiable way.

**RC 5** *Formalizing Knowledge into a Machine-Readable Structure*: To achieve the vision of fully networked cyber-physical systems, one of the main requirements is to semantically network the multitude of different devices and systems and to integrate their data as a basis for decision-making. One example is the processing of information from condition monitoring systems [41]. To do this, it is necessary to formalize corresponding knowledge into a machine-readable structure. The definition of domain knowledge in an ontological structure is an essential, but time-consuming and complex process. A major problem in creating interoperable semantic descriptions in constantly evolving systems is the resulting semantic heterogeneity. Therefore, semantic concepts from different parties must be integrated with each other and ambiguities need to be removed [42].

**RC 6** *Semantic Data Integration and Analysis* is a central challenge of modern CPSs. It requires the dissolution of data silos and the integration of legacy databases, as they often occur in grown structures. Concurrently, solutions must be found to deal with outdated, incorrect, and duplicated data sets. Conventional, centralized approaches such as the traditional Extract-Transform-Load (ETL) process are too inflexible and rigid in this respect.

#### 2.3.3 Solution outlines

**RC 4: Unique Identification and Semantic Interoperability of CPS Resources:** In RDF, each resource is identified by an Internationalized Resource Identifier (IRI). To achieve unique identification within the AI-CPPS environment, each resource is assigned an identifier in the form of a Uniform Resource Identifier (URI), a subform of IRI. In the AI-CPPS context, all material and non-material components are referred to as resources. These include, for example, physical components such as machines, sensors and actors, but also documents, software services or internet resources.

**RC 5: Formalizing Knowledge into a Machine-Readable Structure:** The fundamental goal of formalizing and defining an ontological knowledge base is to represent information in a machine-readable form. On this basis, new, implicit facts can then be inferred by reasoning engines. To reduce the effort for ontological modelling of the AI-CPPS environment, both W3C recommendations and industry standards are used in addition to individual domain ontologies. Examples are the Semantic Sensor Network Ontology (SSN)[5] or the Web of Things (WoT) Thing Description[6] or, for the field of industrial manufacturing, the OPC-UA Companion Specification.[7] The use of widespread ontological standards also simplifies the rapid integration of new concepts that become necessary, for example, due to changes in the physical layer. Hence, it is much easier to keep the ontological knowledge base up to date. To resolve the problem of semantic heterogeneity, where the same facts are expressed in different ways, AI-CPPS uses specific ontology matching techniques to merge ontologies [43].

**RC 6: Semantic Data Integration and Analysis:** To integrate the heterogeneous data silos, AI-CPPS uses the *ontology-based integration approach* (*OBDI*), where the different databases are described in a common ontological structure [44]. Central data access to the various data in AI-CPPS takes place via a knowledge graph structure. Queries are submitted by using the SPARQL query language and federated via the graph into the respective database languages of the databases (e.g., SQL). The query result is then returned as an SPARQL result. This virtual data integration

**2** https://www.w3.org/TR/rdf-concepts/.
**3** https://www.w3.org/TR/rdf-schema/.
**4** https://www.w3.org/TR/owl2-overview/.
**5** https://www.w3.org/TR/vocab-ssn/.
**6** https://www.w3.org/TR/wot-thing-description/.
**7** https://opcfoundation.org/about/opc-technologies/opc-ua/ua-companion-specifications/.

means that the databases themselves do not need to be modified and no knowledge about the individual data silos is required when formulating the global query, as the central vocabulary of the knowledge graph can be used for query formulation instead [45].

## 2.4 Human actors and CPS

### 2.4.1 Problem statement

While the automated processes in CPS are addressed in Layer A, the humans involved and their interaction with the CPS should not be neglected either, as a lack of representation of the complex heterogeneous actors results in lower realism and can thus lead to higher planning uncertainty, lower adaptability as well as performance degradation [46, 47]. In the past, however, people have usually either not been included in the modeling process at all or have only been considered as simple actors with homogeneous characteristics that have a predictable influence on processes themselves [48, 49]. Furthermore, if there is a need to adapt behavior of human actors the factors impacting people's decision-making must be known and modeled to a certain extent. However, appropriate representation of human actors is not a trivial task, as their behavior is influenced by a variety of external and internal factors (e.g., needs, intentions, preferences, motivations, skills, perceptions, or options) [50]. Agent-based modeling can be used to model actors involved as digital human twins. The integration of cognitive processes, such as perception, information processing and decision-making has already been established in [51].

In addition, we need a structural representation of environments containing CPS in which both agent-generated demand and the supply of services by different providers can be brought together. This can be, for example, mobility by public transport or the short-term logistics of supply chains to individual orders. This is important to test different strategies to optimize time-efficiency, cost-effectiveness, and environmental footprint. These solutions should also be flexible in the face of short-term changes in demand and capacity shortfalls. In the resulting model, emergent effects might also be identified and investigated. One application scenario is further described in Section 3.2.

### 2.4.2 Research challenges

**RC** 7 *Agent-Based Modeling and Psychological and Behavioral Theories*: By representing human actors using agent-based modeling techniques, the overall system becomes more complex, partly due to emergent effects, which can lead to less transparency and thus a lack of trust. In addition, the modeling process itself often appears arbitrary, since it requires assumption about, e.g., which factors influence decision-making and which rules generally apply to decision-making and action execution [52]. Therefore, one of the challenges that arises in this layer is the explainability of the models.

**RC 8** *Transferring Agent-Based Models to Different Application Areas, Contexts or Populations:* An essential requirement for the described model is its transferability to different application areas and scenarios. The complexity of agent-based models for the adequate representation of human actors can hinder the transferability as well as the scalability of the model (runtime, resources). Therefore, developing methods for developing distributed AI in the context of CPPS is another challenge. One research question here is how distributed and autonomous learning intelligent subsystems can aggregate knowledge in the presence of limited channel capacity [53] to generate knowledge growth in the overall system [54]. Distributed and incremental learning [55] have various advantages over classical centralized methods. Sharing model knowledge instead of raw data allows global learning even in application domains where sufficient communication infrastructure has not been available so far. Furthermore, sharing model knowledge only allows for better privacy protection [56]. There are still open research questions in the development of information-theoretic metrics to evaluate the quality of the developed distributed AI systems in terms of their mutual information during learning in combination with the limited communication channels. A further research question here is how model knowledge can be transferred [57] between different systems using a transformation between systems model knowledge. Through this, for example, model knowledge in one system could be further used and improved in a similar system. Thus, it must be investigated whether the modeling of human actors in AI-CPPS can be generalized in a way that it can be used in different environments with as little adaption effort as possible. One approach could be reducing the complexity of the modeling without neglecting the adaptation to a specific scenario.

**RC 9** *Interdependence between System and Human Actor Behavior:* The behavior of human actors within a AI-CPPS can have a massive impact on its performance and efficiency. Particularly challenging is the mutual interference between human actors and other components of the system. On the one hand, human actors can be encouraged by techniques such as nudging to make better decisions with respect to the overall system, while on the other hand, the behavior of the system with respect to usability, availability, or costs in turn influences the decisions of users [58]. Furthermore, the system must be able to respond to short-term changes caused by spontaneous and unexpected decisions of human agents. So, there is a tradeoff between optimal performance with fixed scheduling and allowing flexibility for short-term adaptations.

### 2.4.3 Solution outlines

**RC 7: Agent-Based Modeling and Psychological and Behavioral Theories:** To enhance the realism of the mapped actors, we use a combination of agent-based modeling and enrich it with well-supported theories from psychology and behaviorism. These theories can be used to specify the behavior of actors to increase the model's *explainability*. For instance, motivational psychology has proposed different approaches to explain motivation and behavior in different situations. Basically, situation-specific (e.g., incentives) and person-specific (e.g., needs, goals) influences are decisive [59]. Integrating these theories, which are often empirically studied repeatedly, should be done in a modular way in order to allow an exchange of these theories if necessary, e.g., with a changing context. Thus, a higher *transferability* of the model is intended, too. A modular structure with defined interfaces to the remaining model components is supposed to achieve a faster development of agent populations for specific scenarios and application areas. Documentation is the key to reproducibility and adaptation of models, i.e., the used theories, submodels and their interaction, as well as input and output of the agent model have to be captured in a structured way (e.g., by using protocols like the ODD [60]).

**RC 8: Transferring Agent-Based Models to Different Application Areas, Contexts or Populations:** We propose one approach which aims to collect human expert knowledge [61] by simple algorithms and easily understandable mathematical operations to ensure transparency and explainability and thus build trust. Knowledge collected in systems is processed for similar systems in order to accelerate the often time-consuming training process through collaborative learning and to improve the speed of adaptation to acute changes across systems. In the course of the investigations, the relationship between information exchange and knowledge growth in the subsystems is also to be examined with regard to their energy efficiency. For this purpose, current approaches to federated or transfer learning, among others, are investigated and extended. The goal is to identify and exploit optimization potentials for the efficient exchange of model or metadata [62].

**RC 9: Interdependence between System and Human Actor Behavior:** The interaction between human actors and CPS has already been addressed by [63] using the example of cyber-physical social systems (CPSS) in passenger transportation systems. Here, the influences of user decisions on the system were demonstrated. Then it was shown how offering single rides and shared rides affects the users decisions and thus the system performance and how pricing can be used to impact decisions. It is planned to further pursue these approaches and to investigate their transferability to other scenarios. To achieve this we plan to build a simulation to verify algorithmic approaches and identify resulting effects. Some of the required information about the spatial structure of the environment to be modeled for the simulation can be obtained for example by selecting, analyzing, and processing OpenStreetMap[8] data, since this provides open access to a wide variety of information.

## 2.5 Concluding remarks

The nine presented research challenges and solution outlines within the three layers of the framework address partially **GC 1** and **GC 3**. Since **GC 2** is an overarching challenge that is relevant in all three layers of the framework, we want to address it here separately. Assessing the resource- and energy efficiency of software in general, and AI-CPPS in particular, is a complex task. However, it gains increased attention in science and society [64, 65], so it also needs to be addressed in this context. The approach we follow is to devise a measurement and analysis model to assess the resource- and energy efficiency. In general, it is based on the work of [66], who described criteria and a measurement model for assessing the resource- and energy efficiency of software products. We apply the work to use cases in the context of AI-CPPS, comparing e.g., different AI models, architectures, and implementations to determine and optimize the software induced energy- and hardware usage [67]. Furthermore, we iterate the model to expand it towards AI-based systems [68]. Making the sustainability metrics and indicators transparent is a first step to include all stakeholders [69, 70] and enable them to develop, distribute, procure, use, optimize, and dispose of the systems sustainably.

**8** https://www.openstreetmap.org/.

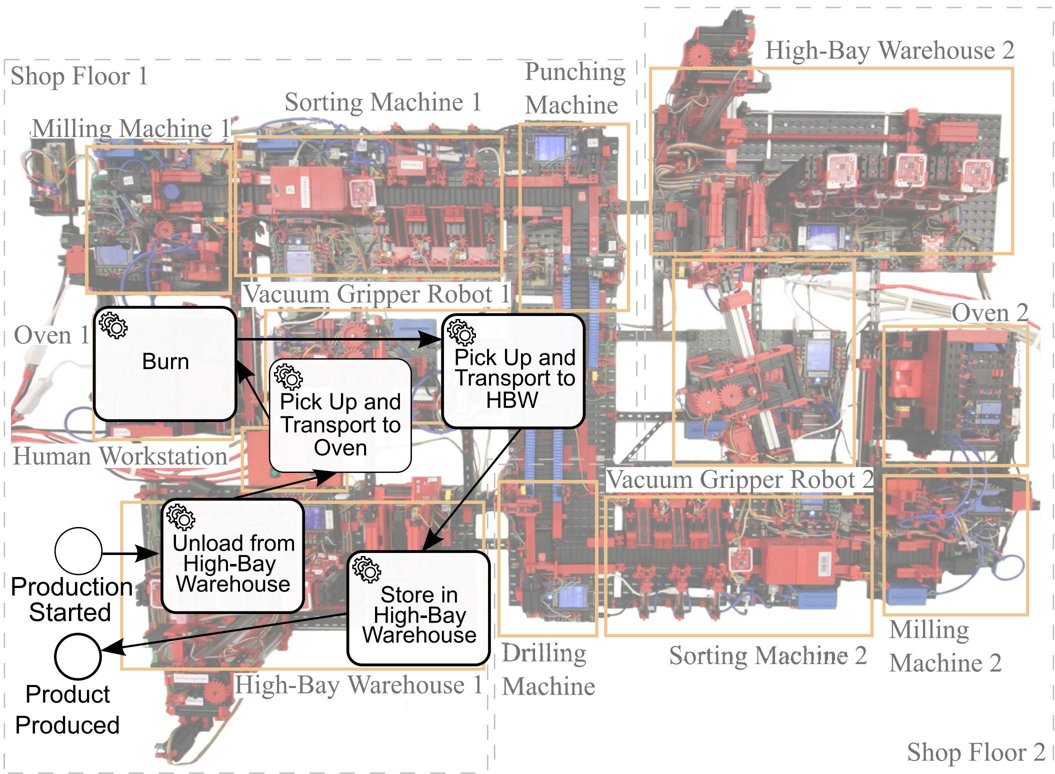


**Figure 2:** Process-based control of the Fischertechnik Smart Factory. (Based on: [9]).

# 3 Application scenarios

To illustrate the previously proposed AI-CPPS framework, two selected application scenarios from classic CPS areas are proposed in the following section. The focus of the generic AI-CPPS framework is to enable the use of advanced AI methods in BPM or other disciplines. By abstracting capabilities from the IoT environment and semantically enriching them, several AI methods can be created, experimentally developed, and tested at both the processes top layer and the bottom layer systems and actors. In the following, we briefly sketch how the proposed challenges from each layer can be concretely addressed and how they can be implemented in a real-world setting.

## 3.1 AI-CPPS in smart manufacturing

Industrial manufacturing with its heterogeneous actuators and sensors, as well as the complex interaction between humans and machines are a main field of application for AI-CPPS. In the following, we present the smart factory used for process-oriented research in the context of smart manufacturing. Figure 2 illustrates the used Fischertechnik smart factory from the University of Trier.[9]

The smart factory is used to simulate production processes at a small-scale while maintaining properties of real-world manufacturing environments, such as runtime behavior and ad-hoc interactions with the physical world [8, 9]. In this context, we use sheet metal production processes as a placeholder for other arbitrary industrial processes.

### 3.1.1 Layer A: processes

In Figure 2, a BPMN process is illustrated that can be executed in the smart factory. We use the *Camunda BPM Platform*[10] as WfMS for modeling and executing production processes. Single activities are modeled as BPMN 2.0 service tasks that invoke a web service that performs the required activity.

**9** Fischertechnik is a company producing modules for small scale simulating factories. Information can be found at https://www.fischertechnik.de/en/simulating/industry-4-0 and information regarding our custom model at https://iot.uni-trier.de.
**10** https://camunda.com/.

#### 3.1.2 Layer B: semantic models

In order to control the smart factory in a process-oriented way, a service-oriented architecture as middleware is needed. The middleware acts as an asset administration shell [39] and, thus, encapsulates and abstracts from low-level control code, enabling simple execution of capabilities in higher-level systems such as WfMSs. In previous work [9, 24], we proposed such a service-oriented architecture. In addition, each web service is semantically enriched by its precondition, effects, and parameters. For example, the actuator of a service is given as a parameter during service invocation. This in turn leads to the fact that the machine resources must also be semantically modeled in a domain ontology. For this purpose, we developed a domain ontology FTOnto [71] that provides knowledge about the entire manufacturing environment and its manufacturing capabilities by using already existing ontologies such as *MAnufacturing's Semantics ONtology* (*MASON*) and *Semantic Sensor Network Ontology* (*SOSA*). MASON is used to describe machines and workstations, and SOSA to formulate the relationships between sensors and actuators as well as the measured data. The alignment of both ontologies thus creates a standards-oriented central knowledge base that can be easily adapted to changes in the physical world.

#### 3.1.3 Layer C: systems and actors

At the bottom layer, the hardware system components and actors are contained. In the smart factory used, machine resources controlled by controllers are the actors in the AI-CPPS. In addition, we integrate a small human workstation with which we emulate human-machine interaction and manual production steps. Besides the integration of humans in the production process, we build a dashboard in which the IoT sensor data streams are depicted for decision support of workers.

### 3.2 AI-CPPS in smart transportation

Residents of rural regions are often dependent on personal cars for everyday errands, leading to inefficient trips and higher environmental pollution. At the same time, online retail is growing and displacing regional suppliers, which further deteriorates local supply and intensifies the problem of inefficient mobility. Intelligent networking of actors with each other and with the public infrastructure according to the architecture of AI-CPPS can counteract these developments.

#### 3.2.1 Layer A: processes

Processes can be used to model, for example, transportation routes of suppliers or for personal traffic routes. This more process-oriented view enables optimization and scheduling of different process activities. In addition, it is possible to build end-to-end processes in which also previously and subsequently required activities are modeled. This end-to-end process view leads to a more profound understanding of the activities and enables targeted decision support for process participants, e.g., by using smart wearables (cf. [25]).

#### 3.2.2 Layer B: semantic models

Within the semantic layer, the knowledge base relevant to this use case must be built. For this purpose, we recommend the use of existing ontologies, e.g., for modeling traffic and weather conditions or public infrastructures. In this way, the data from the different private and public sources can be interlinked and combined to make higher-value decisions [72].

#### 3.2.3 Layer C: system and actors

At the lower AI-CPPS level, it is necessary to model the scenario with its different actors including their objectives, demands, and supplies. The (human) actors and their cognitive activities can be modeled using, e.g., the BDI agent architecture [73]. Another central component is the representation of the spatial structure of the region under consideration. This can be achieved using data from publicly available sources such as OpenStreetMap,[11] as described in Section 2.3. Based on such a model, the situation in the real world can then be virtually simulated.

## 4 Conclusions

In this paper, we discussed the need for process-oriented CPSs and presented a generic framework for AI-CPPSs. At the beginning, three general challenges (cf. **GC 1**–**GC 3**) of the creation of explainable, resource-efficient and flexible CPSs are described. The introduced framework is divided into three layers, for which three specific research challenges and the respective solution outlines were

11 https://www.openstreetmap.org/.

discussed. Within *Layer A*, process modeling, execution, and analysis take place. The modeling and execution of IoT-based cyber-physical processes is supported by AI methods like CBR and AI planning to reuse experiential knowledge (cf. [13, 14]). Within *Layer B*, the physical actors as well as their data and involved systems are described in a machine-understandable and unique form. Within an ontological knowledge base, the entire AI-CPPS environment is described by applying existing standards and their alignment. In addition to classic CPS components, such as actuators or sensors, *Layer C* focuses especially on the role of human actors. To achieve this, AI-CPPSs use agent-based modelling methods to simulate human actors in complex environments. Finally, two selected scenarios from the fields of manufacturing and intelligent transport were presented to illustrate our framework. In this way, the AI-CPPS framework provides a basic approach to the design of process-aware, adaptive, and sustainable CPSs and combines different research areas such as Green Artificial Intelligence, Business Process Management, or Agent-Based Modeling. However, adapting the presented framework to the real world is not a trivial task. As the example scenarios for manufacturing and transportation presented in Section 3 show, each application requires further research to extend and specify the described model. Another challenge is that, unlike application in a modeled environment, which allows evaluation of the framework under controlled conditions, real-world scenarios require bringing together many actors with different preferred technologies. Therefore, it is necessary to further investigate the iterative integration of different actors and technologies in the given application areas. Furthermore, in the future, the AI-CPPS framework is to be applied to further CPS application areas and the solution outlines described in the various layers are to be worked out and implemented.

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## References

[1] E. A. Lee, "Cyber physical systems: design challenges," in *2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC)*, IEEE, 2008, pp. 363—369.

[2] R. Rajkumar, "A cyber—physical future," *Proc. IEEE*, vol. 100, pp. 1309—1312, 2012.

[3] E. Sisinni, A. Saifullah, S. Han, U. Jennehag, and M. Gidlund, "Industrial internet of things: challenges, opportunities, and directions," *IEEE Trans. Ind. Inf.*, vol. 14, no. 11, pp. 4724—4734, 2018.

[4] M. Reichert and B. Weber, *Enabling Flexibility in Process-Aware Information Systems - Challenges, Methods, Technologies*, Berlin, Heidelberg, Springer, 2012.

[5] I. Beerepoot, C. Di Ciccio, H. A. Reijers, et al., "The biggest business process management problems to solve before we die," *Comput. Ind.*, vol. 146, p. 103837, 2023.

[6] C. Janiesch, A. Koschmider, M. Mecella, et al., "The internet of things meets business process management: a manifesto," *IEEE Syst. Man Cybern. Mag.*, vol. 6, no. 4, pp. 34—44, 2020.

[7] J. Erasmus, I. Vanderfeesten, K. Traganos, and P. W. P. J. Grefen, "The case for unified process management in smart manufacturing," in *22nd EDOC*, IEEE, 2018, pp. 218—227.

[8] L. Malburg, R. Seiger, R. Bergmann, and B. Weber, "Using physical factory simulation models for business process management research," in *BPM Workshops, LNBIP*, vol. 397, Springer, 2020, pp. 95—107.

[9] R. Seiger, L. Malburg, B. Weber, and R. Bergmann, "Integrating process management and event processing in smart factories: a systems architecture and use cases," *J. Manuf. Syst.*, vol. 63, pp. 575—592, 2022.

[10] L. Malburg, M. Hoffmann, and R. Bergmann, "Applying MAPE-K control loops for adaptive workflow management in smart factories," *J. Intell. Inf. Syst.*, pp. 1—29, 2023. https://doi.org/10.1007/s10844-022-00766-w.

[11] J. Lee, H. A. Kao, and S. Yang, "Service innovation and smart analytics for industry 4.0 and big data environment," *Proc. CIRP*, vol. 16, pp. 3—8, 2014.

[12] M. Beetz, R. Chatila, J. Hertzberg, and F. Pecora, "AI reasoning methods for robotics," in *Handbook of Robotics*, Cham, Springer, 2016, pp. 329—356.

[13] L. Malburg and R. Bergmann, "Towards adaptive workflow management by case-based reasoning and automated planning," in *30th ICCBR Workshops*, CEUR-WS.org, 2022. Accepted for Publication.

[14] L. Malburg, F. Brand, and R. Bergmann, "Adaptive management of cyber-physical workflows by means of case-based reasoning and automated planning," in *26th EDOC Workshops. LNBIP*, Springer, 2023. Accepted for Publication.

[15] A. Marrella, "Automated planning for business process management," *J. Data Semant.*, vol. 8, no. 2, pp. 79—98, 2019.

[16] A. Marrella, M. Mecella, and S. Sardiña, "Intelligent process adaptation in the SmartPM system," *ACM Trans. Intell. Syst. Technol.*, vol. 8, no. 2, pp. 25:1—25:43, 2017.

[17] C. G. Cassandras, “Smart cities as cyber-physical social systems,” *Engineering*, vol. 2, no. 2, pp. 156—158, 2016.

[18] N. Zhang, “Smart logistics path for cyber-physical systems with internet of things,” *IEEE Access*, vol. 6, pp. 70808—70819, 2018.

[19] L. Bottou, “From machine learning to machine reasoning,” *Mach. Learn.*, vol. 94, no. 2, pp. 133—149, 2014.

[20] T. Santarius, J. C. T. Bieser, V. Frick, et al., “Digital sufficiency: conceptual considerations for icts on a finite planet,” *Ann. Telecommun.*, 2022. https://doi.org/10.1007/s12243-022-00914-x.

[21] J. Mendez, K. Bierzynski, M. P. Cuéllar, and D. P. Morales, “Edge intelligence: concepts, architectures, applications, and future directions,” *ACM Trans. Embed. Comput. Syst.*, vol. 21, no. 5, pp. 1—41, 2022.

[22] T. Rahwan, T. P. Michalak, M. Wooldridge, and N. R. Jennings, “Coalition structure generation: a survey,” *Artif. Intell.*, vol. 229, pp. 139—174, 2015.

[23] M. Dumas, M. La Rosa, J. Mendling, and H. A. Reijers, *Fundamentals of Business Process Management*, Berlin, Heidelberg, Springer, 2018.

[24] L. Malburg, P. Klein, and R. Bergmann, “Semantic web services for AI-research with physical factory simulation models in industry 4.0,” in *1st International Conference Innovative Intelligent Industrial Production and Logistics (IN4PL)*, SciTePress, 2020, pp. 32—43.

[25] S. Schönig, L. Ackermann, S. Jablonski, and A. Ermer, “IoT meets BPM: a bidirectional communication architecture for IoT-aware process execution,” *Software Syst. Model*, vol. 19, no. 6, pp. 1443—1459, 2020.

[26] W. van der Aalst, A. Adriansyah, A. Karla Alves de Medeiros, et al., “Process mining manifesto,” in *BPM Workshops*, Springer, 2012, pp. 169—194.

[27] C. Chang, S. N. Srirama, and R. Buyya, “Mobile cloud business process management system for the internet of things: a survey,” *ACM Comput. Surv.*, vol. 49, no. 4, pp. 70:1—70:42, 2017.

[28] V. Torres, E. Serral Asensio, P. Valderas, V. Pelechano, and P. W. Grefen, “Modeling of IoT devices in business processes: a systematic mapping study,” in *22nd CBI*, IEEE, 2020, pp. 221—230.

[29] P. Valderas, V. Torres, and E. Serral Asensio, “Modelling and executing IoT-enhanced business processes through BPMN and microservices,” *J. Syst. Software*, vol. 184, p. 111139, 2021.

[30] A. del Río-Ortega, M. Resinas, C. Cabanillas, and A. Ruiz-Cortés, “On the definition and design-time analysis of process performance indicators,” *Inf. Syst.*, vol. 38, no. 4, pp. 470—490, 2013.

[31] C. W. Günther and E. Verbeek, *XES Standard Definition - Version 2.0*, 2014.

[32] J. Grüger, L. Malburg, J. Mangler, et al., “SensorStream: an XES extension for enriching event logs with IoT-sensor data,” CoRR abs/2206.11392, 2022.

[33] J. Mangler, J. Grüger, L. Malburg, et al., “DataStream XES extension: embedding IoT sensor data into extensible event stream logs,” *Future Internet*, vol. 15, no. 3, p. 109, 2023.

[34] G. Müller, *Workflow Modeling Assistance by Case-Based Reasoning*, Wiesbaden, Springer, 2018.

[35] IBM, *An Architectural Blueprint for Autonomic Computing: Autonomic Computing White Paper*, New York, IBM, 2006.

[36] M. Hoffmann, L. Malburg, and R. Bergmann, “ProGAN: toward a framework for process monitoring and flexibility by change via generative adversarial networks,” in *BPM Workshops, LNBIP*, vol. 436, Springer, 2022, pp. 43—55.

[37] R. Seiger and U. Aßmann, “Consistency and synchronization for workflows in cyber-physical systems,” in *10th ICCPS*, ACM, 2019, pp. 312—313.

[38] R. Seiger, S. Huber, P. Heisig, and U. Aßmann, “Toward a framework for self-adaptive workflows in cyber-physical systems,” *Software Syst. Model*, vol. 18, no. 2, pp. 1117—1134, 2019.

[39] A. Perzylo, J. Grothoff, L. Lucio, et al., “Capability-based semantic interoperability of manufacturing resources: a BaSys 4.0 perspective,” *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 1590—1596, 2019.

[40] M. Yahya, J. G. Breslin, and M. I. Ali, “Semantic web and knowledge graphs for industry 4.0,” *Appl. Sci.*, vol. 11, no. 11, p. 5110, 2021.

[41] F. Theusch, P. Klein, R. Bergmann, W. Wilke, W. Bock, and A. Weber, “Fault detection and condition monitoring in district heating using smart meter data,” in *PHM Society European Conference*, vol. 6, 2021, pp. 407—417.

[42] J. Euzenat and P. Shvaiko, *Ontology Matching*, Berlin, Heidelberg, Springer, 2007.

[43] P. Shvaiko and J. Euzenat, “Ontology matching: state of the art and future challenges,” *IEEE Trans. Knowl. Data Eng.*, vol. 25, no. 1, pp. 158—176, 2011.

[44] H. Wache, T. Voegele, U. Visser, et al., “Ontology-based integration of information-a survey of existing approaches,” in *Ois@ ijcai*, 2001.

[45] F. Ekaputra, M. Sabou, E. Serral Asensio, E. Kiesling, and S. Biffl, “Ontology-based data integration in multi-disciplinary engineering environments: a review,” *Open J. Inf. Syst.*, vol. 4, no. 1, pp. 1—26, 2017.

[46] I. Gräßler, D. Wiechel, and D. Roesmann, “Integrating human factors in the model based development of cyber-physical production systems,” *Proc. CIRP*, vol. 100, pp. 518—523, 2021.

[47] A. M. Madni, “Integrating humans with software and systems: technical challenges and a research agenda,” *Syst. Eng.*, vol. 13, no. 3, pp. 232—245, 2010.

[48] J. Boudreau, W. Hopp, J. O. McClain, and L. J. Thomas, “On the interface between operations and human resources management,” *Manuf. Serv. Oper. Manag.*, vol. 5, no. 3, pp. 179—202, 2003.

[49] I. Gräßler, D. Roesmann, and J. Pottebaum, “Model based integration of human characteristics in production systems: a literature survey,” *Proc. CIRP*, vol. 99, pp. 57—62, 2021.

[50] S. K. Sowe, E. Simmon, K. Zettsu, F. De Vaulx, and I. Bojanova, “Cyber-physical-human systems: putting people in the loop,” *IT Prof.*, vol. 18, no. 1, pp. 10—13, 2016.

[51] E. Bonabeau, “Agent-based modeling: methods and techniques for simulating human systems,” *Proc. Natl. Acad. Sci.*, vol. 99, no. 3, pp. 7280—7287, 2002.

[52] T. Balke and N. Gilbert, “How do agents make decisions? a survey,” *J. Artif. Soc. Soc. Simulat.*, vol. 17, no. 4, p. 13, 2014.

[53] C. E. Shannon, “A mathematical theory of communication,” *Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379—423, 1948.

[54] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-efficient learning of deep networks from decentralized data,” in *Artificial Intelligence and Statistics*, Fort Lauderdale, PMLR, 2017, pp. 1273—1282.

[55] R. Lipp, A. Schmeink, G. Dartmann, et al., “Incremental parameter estimation of stochastic state-based models,” in *2021 IEEE 19th World Symposium on Applied Machine Intelligence and Informatics (SAMI)*, IEEE, 2021, pp. 000317—000322.

[56] S. Truex, N. Baracaldo, A. Anwar, et al., "A hybrid approach to privacy-preserving federated learning," in *Proceedings of the 12th ACM Workshop on Artificial Intelligence and Security*, 2019, pp. 1—11.
[57] K. Weiss, T. M. Khoshgoftaar, and D. Wang, "A survey of transfer learning," *J. Big Data*, vol. 3, no. 1, pp. 1—40, 2016.
[58] J. S. Mertoguno, "Human decision making model for autonomic cyber systems," *Int. J. Artif. Intell. Tool.*, vol. 23, no. 06, p. 1460023, 2014.
[59] J. Heckhausen and H. Heckhausen, Eds. *Motivation und Handeln*, Berlin, Springer-Lehrbuch, Springer, 2018. 5. überarbeitete und erweiterte auflage edn.
[60] V. Grimm, U. Berger, D. L. DeAngelis, J. G. Polhill, J. Giske, and S. F. Railsback, "The odd protocol: a review and first update," *Ecol. Model.*, vol. 221, no. 23, pp. 2760—2768, 2010.
[61] M. Maier, H. Kunstmann, R. Zwicker, A. Rupenyan, and K. Wegener, "Autonomous and data-efficient optimization of turning processes using expert knowledge and transfer learning," *J. Mater. Process. Technol.*, vol. 303, p. 117540, 2022.
[62] F. Chen, M. Luo, Z. Dong, Z. Li, and X. He, "Federated meta-learning with fast convergence and efficient communication," arXiv preprint arXiv:1802.07876, 2018.
[63] M. Dziubany, J. Schneider, A. Schmeink, and G. Dartmann, "Optimization of a cpss-based flexible transportation system," in *2020 9th Mediterranean Conference on Embedded Computing (MECO)*, IEEE, 2020, pp. 1—5.
[64] J. Mulrow, M. Gali, and E. Grubert, "The cyber-consciousness of environmental assessment: how environmental assessments evaluate the impacts of smart, connected, and digital technology," *Environ. Res. Lett.*, vol. 17, no. 1, p. 013001, 2021.
[65] R. Verdecchia, P. Lago, and C. de Vries, "The future of sustainable digital infrastructures: a landscape of solutions, adoption factors, impediments, open problems, and scenarios," *Sustain. Comput.: Inform. Syst.*, vol. 35, p. 100767, 2022.
[66] E. Kern, L. M. Hilty, A. Guldner, et al., "Sustainable software products—towards assessment criteria for resource and energy efficiency," *Future Generat. Comput. Syst.*, vol. 86, pp. 199—210, 2018.
[67] A. Guldner, S. Kreten, and S. Naumann, "Exploration and systematic assessment of the resource efficiency of Machine Learning," in *INFORMATIK 2021 - Computer Science & Sustainability*, *Lecture Notes in Informatics (LNI)*, Gesellschaft für Informatik, 2021, pp. 287—299.
[68] A. Guldner and J. Murach, "Measuring and assessing the resource and energy efficiency of artificial intelligence of things devices and algorithms," in *Advances and New Trends in Environmental Informatics*, Cham, Springer International Publishing, 2022, pp. 185—199.
[69] A. Guldner, E. Kern, S. Kreten, and S. Naumann, "Criteria for sustainable software products: analyzing software, informing users, and politics," in *Software Sustainability*, Cham, Springer International Publishing, 2021, pp. 17—42.
[70] S. Naumann, A. Guldner, and E. Kern, "The eco-label blue angel for software—development and components," in *Progress in IS*, A. Kamilaris, V. Wohlgemuth, K. Karatzas, and I. N. Athanasiadis, Eds., Cham, Springer International Publishing, 2020, pp. 79—89.
[71] P. Klein, L. Malburg, and R. Bergmann, "FTOnto: a domain ontology for a Fischertechnik simulation production factory by reusing existing ontologies," in *21st Conference on Lernen, Wissen, Daten, Analysen (LWDA)*, vol. 2454, CEUR-WS.org, 2019, pp. 253—264.
[72] A. De Nicola and M. L. Villani, "Smart city ontologies and their applications: a systematic literature review," *Sustainability*, vol. 13, no. 10, p. 5578, 2021.
[73] A. S. Rao and M. P. Georgeff, "Bdi agents: from theory to practice," in *ICMAS*, vol. 95, Melbourne, AAAI, 1995, pp. 312—319.

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