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Cognitive systems and interoperability in the enterprise: A systematic literature review

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ABSTRACT

The transition from automated processes to mechanisms that manifest intelligence through cognitive abilities such as memorisation, adaptability and decision-making in uncertain contexts, has marked a turning point in the field of industrial systems, particularly in the development of cyber–physical systems and digital twins. This evolution, supported by advances in cognitive science and artificial intelligence, has opened the way to a new era in which systems are able to adapt and evolve autonomously, while offering more intuitive interaction with human users. This article proposes a systematic literature review to gather and analyse current research on Cognitive Cyber–Physical Systems (CCPS), Cognitive Digital Twins (CDT), and cognitive interoperability, which are pivotal in a contemporary Cyber–Physical Enterprise (CPE). From this review, we first seek to understand how cognitive capabilities that are traditionally considered as human traits have been defined and modelled in cyber–physical systems and digital twins in the context of Industry 4.0/5.0, and what cognitive functions they implement. We explore their theoretical foundations, in particular in relation to cognitive psychology and humanities definitions and theories. Then we analyse how interoperability between cognitive systems has been considered, leading to cognitive interoperability, and we highlight the role of knowledge representation and reasoning.

1. Introduction

The rapid growth of technology in recent decades has not only redefined our understanding of enterprise systems as complex systems that require integration and interoperability to function effectively (Morel et al., 2007), but also their interaction with the environment. Much effort is currently put into technologies to sense the environment, digitalise observed systems and maintain a link between the physical and the digital/cyber components. The introduction of *Cyber–Physical Systems* (CPS) and *Digital Twin* (DT) technologies, together with advances in Information and Communication Technologies (ICT), has been the major driving force for the 4th industrial revolution (Arnold et al., 2016-06). The term CPS refers to a generation of systems with integrated computational and physical capabilities (Lezoche & Panetto, 2020) that possesses three basic capabilities (Cardin, 2019): intelligence (computation), connectedness (communication), and responsiveness (control). On the other hand, the DT provides a thorough physical and digital representation, detailing key characteristics and actions of a given component, product, or system (Abburu et al., 2020b; Boschert et al., 2018), to predict failures and opportunities for changing, to prescribe real time actions for optimising and/or mitigating unexpected events (Semeraro et al., 2021). Both CPS and DT are becoming an established part of the modern industry (Gaffinet et al., 2023), complementing each other and building overall enterprise systems where each physical part can potentially be coupled with a digital replica.

The future industry tends to become a Cyber–Physical Enterprise (CPE) (Panetto et al., 2019), which consists of autonomous and cooperative technical elements, humans and sub-organisations that are connected based on the context within and across all levels of the global organisation, from processes, through machines and up to enterprises and supply-chains networks. The operation of a CPE increases the complexity to be managed by organisations and, consequently, the requirements for interoperability, which refers to the fundamental ability of different computerised products or systems to connect and exchange information without restriction, either in terms of implementation or access. Interoperability is recognised as an essential requirement for Systems-of-Systems (Panetto et al., 2016) and CPE (Panetto et al., 2019). But because of its specificity with autonomous and cooperative components, a CPE requires CPS with advanced capabilities with some level of intelligence. This is especially required to cooperate

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efficiently with human agents. Indeed, the understanding of information exchanged between two entities is the concern of conceptual, or semantic interoperability. Recognised as the most problematic among the seven types of interoperability issues faced by any collaboration (Panetto, 2007), *semantic interoperability* is about attaching meaning (semantics) to information, thus transforming it into knowledge that can be shared with a common understanding between entities or agents, be they artificial (machines, computers, …) or non-artificial (humans, …). This type of interoperability is generally implemented using knowledge graphs (e.g. ontology), which formalise concepts, relationships, and axioms, thus defining the domain of discourse (Liu & Özsu, 2009). They provide a formal representation of knowledge that machines can theoretically process in the same way. Today ontology-based solutions ensure that technological components (CPS) of a CPE share a common vocabulary and can reason on exchanged knowledge. However, machine-readable ontologies are not readable the same way by humans, who may have different interpretations from those of machines, simply because they do not necessarily understand all the formalism and have specific ways of reasoning and interpreting, which may also differ from one individual to another. Consequently, relying on ontologies is not always enough to ensure CPS and human agents understanding each other enough to cooperate or collaborate efficiently in a CPE context. Reaching a mutual understanding allowing collaboration implies not only interpreting the semantics (meaning) but understanding its contecy and the way it is interpreted (reasoning), leading to actions, thus sharing a cognitive process. However, the common understanding of a situation allowing collaboration between a set of heterogeneous entities might require more features, and in particular cognitive entities and cognitive interoperability (Naudet et al., 2023).

In this context, the aim of Artificial Intelligence (AI) is to equip artificial systems with abilities to process information and knowledge, learn, reason and make decisions (Tien, 2017). However, given the complexity, unpredictability and richness of the human life, as well as the multiple problems we tackle on a daily basis, it is clear that machines, regardless of their artificial intelligence, cannot fully emulate or replace humans. With this in mind, the integration of anthropomorphism can facilitate a better symbiosis between human and machine (Waytz et al., 2010). In particular if machines should have human-like mental processes, this underlines the importance of infusing AI systems with elements of human cognition, creating a seamless integration that exploits the best of both worlds. In 2018, the IoT European Research Cluster highlighted that the next generation IoT should take a more human-centred perspective, where intelligent objects have social capabilities allowing seamless interaction between autonomous systems and humans (Vermesan et al., 2018). Similarly, on the cyber–physical systems side, it has been argued recently that a CPS misses a "Social" component to become a Cyber–Physical–Social System (CPSS), able to collaborate with humans at the same level humans would do (Yilma et al., 2021-08). Artificial systems, with cognitive capabilities, cannot only perform tasks but also grasp context, anticipate challenges and collaborate effectively with their human counterparts (Schuetz & Venkatesh, 2020).

Cognition is mainly about knowledge and understanding. Although it is a research subject by itself, we can refer to a well admitted definition used in human experimental psychology: "*Cognition is all the processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used*" (Neisser, 1967). These *cognitive processes or functions* refer to the mental processes involved in acquiring knowledge, manipulating information and reasoning (Kiely, 2014), and include *perception*, *attention*, *memory*, *learning*, *reasoning*, *problem-solving*, *decision-making* and *situational awareness* (Vernon et al., 2007). As essential aspects of cognition, memorisation and the capability of learning allow to manage knowledge, reason on it, and take decisions. With the advent of computing, it became clear that computers, when properly programmed, have the potential to simulate this human ability (Seth, 2021), and this is the basis of *computational cognition* or *cognitive computing* (Zheng et al., 2017-01-16). Although the first attempts at implementation date back to the mid-twentieth century, the technological constraints of the time prevented any further development. Today, with computers becoming ever more compact, powerful and fast, cognitive models are finding their way into a variety of fields, from medicine and industry to physical systems and the analysis of large masses of data. The 2020 report of the World Manufacturing Foundation on Manufacturing and AI[1] highlights collaborative intelligence where humans and AIs collaborate. AI cognition is considered through six components: learning, knowledge representation and reasoning, automated planning, natural language processing, perception. From the human perspective, it is highlighted that AI can expand human cognition capabilities or taking it into account for tailored training and (re)skilling of workers. However, the collaboration between human and AI supported by cognitive interactions is not yet addressed. There are different approaches or technologies qualified with the "cognitive" adjective and that implement partially cognitive functions in industry 4.0/5.0 systems, however all have been qualified as *cognitive systems*. When they reach a level of complexity that enables interaction similar to that observed between humans, cognitive systems realise the human–machine symbiosis paradigm. In this context, the machine does not work for or in place of the human, but collaboratively or symbiotically (Vermesan et al., 2022) with him.

The aspiration to create systems that not only "understand" and "learn" from their interactions but can also dynamically adapt to the changing needs of the user and ultimately collaborate with humans leads progressively to an evolution of the Industry 4.0/5.0 technological pillars. The *Cognitive IoT* (Vermesan et al., 2018) has emerged some time ago in the Internet of Things (IoT) community, while *Cognitive Cyber–Physical Systems* (CCPS) and *Cognitive Digital Twins* (CDT) have been explored by researchers in enterprise systems. This study focuses on CCPS and CDT, leaving CIoT out of our scope. CCPS, integrating closed-loop solutions with cybernetic and physical components equipped with cognitive properties (Topal et al., 2020), stands out as a natural progression within this technological trajectory. The scope of CCPS applications covers areas such as human–robot synergy, transportation system optimisation, advanced industrial process automation, precision healthcare, and smart agriculture (John et al., 2021). CDT adds capabilities to an industrial system, by representing the virtual replica of a cognitive entity or process or adding cognitive abilities to it. Both CCPS and CDT being cognitive systems, they are equipped with an artificial intelligence that in particular enables reasoning, decision-making and autonomy. It is not just a static digital replica, but a dynamic, learning and evolving one. It predicts and adapts to change, facilitating a deeper level of teamwork and interaction. The inherent attributes of CCPS include their ability to compute anywhere, connect widely, reconfigure dynamically, automate at high levels, and operate in a range from fully manual and supervised to fully independent and autonomous (John et al., 2021). Not only do CDTs anticipate and adapt to the requirements of their real-world partners, but CCPS also use these innovations to efficiently execute complex operations in a variety of fields. This efficiency is greatly enhanced by the use of Knowledge Representation and Reasoning (KRR) technologies, which enable a significant degree of independence and context awareness, due to their dynamic nature and complex reasoning capability (Liu et al., 2022). Indeed the exploitation of KRR by CCPS and CDT takes advantage of advances in semantic technologies for reasoning and adaptation, but also to establish semantic interoperability. Ontology ensures that CCPS technological components share a common vocabulary, which is a prerequisite for CCPS and CDT to reason about the knowledge exchanged. Knowledge graphs then enable CDT to capture the dynamics and interactions within complex environments (Kharlamov et al., 2018), facilitating better understanding and collaboration between machines and humans (Zheng et al., 2022).

[1] https://worldmanufacturing.org/report/report-2020/

1.1. Outcomes from previous expert review

The present article was initiated by an expert review focusing on cognitive interoperability and its enablers, in Industry 5.0 settings where human–machine collaboration is sought (Naudet et al., 2023). It focuses on a subpart of what was addressed in this preliminary work: cognitive CPS, DT, and Interoperability. The goal of the SLR here is to go deeper in this focus, extracting the complete state-of-the-art on the subject as of today, and analysing it to answer the set of research questions we list in the following section.

The important points highlighted by the expert review are the following. The article delves into the cognitive dimension of human–machine interaction, highlighting how human mental processes such as attention, language, learning, memory, perception, and thought (Neisser, 1967) are crucial for knowledge management and decision-making. It addresses social cognition, related to the theory of mind (Bradford et al., 2015), and its significance in interpreting the intentions and actions of others, referencing motor and perceptual resonance (Wykowska et al., 2016). It then looks at cognitive interoperability within the realm of AI, where human–machine collaboration is pivotal for the creation of collaborative cognitive agents, an area known as cogni-culture (Pimplikar et al., 2017). Naudet et al. underscore the challenges of Hybrid Intelligence (HI), which seeks to balance and learn from the interaction between humans and AI (Akata et al., 2020), and compares it with Augmented Hybrid Intelligence (AHI), which involves combining human and AI cognitive capabilities for optimal complementarity, especially through systems based on cognitive computing (Zheng et al., 2017-01-16). The discussion also encompasses how cognitive systems and cognitive computing aim to mimic human interaction for better human–computer symbiosis (Vermesan et al., 2018), and how cognitive architectures are crucial to enable these systems to observe, learn, and empathise (Sathi, 2016). Referring to cognitive objects, it is highlighted how the IoT can be utilised to augment human intelligence by using technology for more natural interactions (Sathi, 2016). The discussion expands to smart objects (Kortuem et al., 2009) and cognitive architectures, connecting to cognitive psychology and neuroscience, and citing models like SOAR (Vernon et al., 2007) and LIDA (Franklin et al., 2016) for simulation. Finally, the article addresses the integration of cognitive functions into Industry 4.0/5.0 through concepts such as Cognitive Automation (Engel et al., 2022), CCPS (Kalaboukas et al., 2021), and CDT (Abburu et al., 2020a, 2020b), highlighting their potential to enhance planning and optimisation in various contexts. Naudet et al. conclude on the importance of cognitive interoperability for collaboration between human operators and CPS, emphasising the need for social and communicative skills that are comprehensible to humans in machines (Castro et al., 2021).

1.2. Scope

In our detailed analysis, we focused on papers that model, implement, study or experiment cognition in industrial systems, especially CPS and DT. These systems are central in a CPE and constitute a crucial part of the modern industrial landscape. Our review strictly emphasises articles that address the many facets of cognition in these systems, ensuring a clear distinction from more general or tangent studies. Our primary attention is centred on understanding the complex layers of cognition's definition, modelling, and implementation as they apply to CPS and Digital Twins. Consequently, articles of brief nature or those not diving deep into the pivotal role of cognition within these specific contexts have been excluded. To deepen our comprehension of cognitive dimensions precisely within these cognitive systems, we prioritised papers that discuss the theoretical foundations for cognitive integration in CPS and DT. We also emphasised studies that address interoperability in cognitive systems and those that highlight KRR as an essential tool for improving cognitive processes and ensuring seamless interoperability in the context of these systems.

1.3. Key research questions

The review protocol implemented in this study follows Kitchenham guidelines (Kitchenham, 2007-01-01) to ensure a systematic review of the literature, which structures the article around specific questions, aligned with the study objectives, to focus the analysis on the main topics of interest. Our study examines how cognitive functions are modelled and implemented in industrial environments, with a focus on CCPS and CDT systems. The aim is to better understand how cognitive aspects are understood, defined and implemented in such systems and how they are used to improve the overall industrial environment's performance and interoperability, particularly in the context of Industry 4.0/5.0. This leads us to the following set of research questions that guided our analysis, related to cognition in CPS and DT and cognitive interoperability:

- **RQ1:** How is cognition characterised and defined in the literature of cognitive psychology and human theories, and to which extent cognitive CPS and DT refer to it in their own perspective?
- **RQ2:** Which cognitive functions are integrated into CPS and DT?
- **RQ3:** What particular methods, strategies or models are used to implement cognition in CPS and DT?
- **RQ4:** What are the theoretical foundations of cognition used in CPS and DT, and how do they help to implement the cognitive processes?
- **RQ5:** How are cognitive CPS and DT conceptualised, implemented, and applied within the context of Industry 4.0?
- **RQ6:** How can interoperability within industrial environments be enhanced by cognition, and is there a concept of cognitive interoperability?
- **RQ7:** What types of knowledge representation and reasoning approaches are commonly used in CPS and DT to structure and manage relevant knowledge for specific cognitive tasks, and facilitate cognitive interoperability?

With these questions in mind, we address in detail the essential aspects of cognition within CCPS and CDT and explore the concept of cognitive interoperability as a fundamental key to effective human-CPS collaboration. Section 2 provides details of the relevant literature extraction strategy, including resource library selection, search query and inclusion/exclusion criteria. Section 3 focuses on the definition of cognition according to cognitive psychology and humanities theories, while exploring how industrial systems interpret and integrate cognition. It also details their specific cognitive characteristics, the strategies used and the theoretical foundations of satisfactory cognitive integration (RQ1, RQ2, RQ3 and RQ4). Section 4 presents the definitions of a CCPS and a CDT in the literature, while exploring (cognitive) interoperability among cognitive components and how KRR supports cognition and interoperability (RQ5, RQ6 and RQ7). Section 5 then offers an in-depth reflection on our results, including a definition of cognitive systems, CCPS and CDTs. Finally, Section 6 concludes with the main results of our study and future perspectives.

2. SLR synthesis

2.1. Methodology

This subsection provides an overview of our approach to selecting relevant papers, including the steps involved in databases selection, defining keywords and search strings, and filtering the papers. The search process encompasses several activities, including the selection of digital libraries, formulation of the search string, execution of a pilot search, refinement of the search string, and retrieval of an initial list of primary studies from the digital libraries that match the search criteria.

Table 1
Number of papers retrieved from each publisher database.

Publisher databases	Number of articles
Scopus	503
Web Of Science	314
IEEE Xplore	175
ACM	64
Pubmed	23
Total	**1079**

2.1.1. Database selection

Prior to the search, it is essential to select an appropriate set of databases to enhance the likelihood of discovering highly relevant articles. To achieve the broadest possible coverage of studies, the most widely used literature databases in the field are explored. A comprehensive and expansive perspective is imperative to encompass a wide range of literature. For our study, we have taken the following digital databases: Web Of Science (WOS); ACM Digital Library; IEEE Xplore; Scopus; Pubmed. We chose to search through five databases, knowing that typically using at least four is considered enough for a thorough literature search (Kitchenham et al., 2010). Notably, Scopus stands out among these five because it is a comprehensive database that collects abstracts and citations from a variety of peer-reviewed journals. The articles sourced from Scopus and WOS are published by a range of well-known publishers, including Elsevier, Springer, Taylor & Francis Online, and IEEE, which helps in enhancing the thoroughness of our research. As is often the case, we anticipate finding duplicate articles in our results, which will be filtered out. it is important to note that each database requires a slightly different approach to query formulation. Therefore, we have adapted the search phrases outlined in Section 2.1.2 accordingly to make sure we get the right results from each database.

2.1.2. Keywords and search strings definition

In order to find the articles allowing to answer our research questions, specific keywords were defined to compose a search string. This string was split into search units and combined by boolean operators. Acronyms, synonyms, and alternate spellings were also included. This way, keywords related to *interoperability*, *digital twin*, and *cyber–physical systems* were interconnected using the boolean operator **AND** with *cognition*, leading to the following query:

*"Cognition" **AND** ("Interoperability" OR "Digital Twin" OR "Cyber–Physical Systems")*

To ensure a comprehensive and systematic exploration of the literature, this search relied primarily on article metadata. Metadata included titles, abstracts, authors and keywords, providing a structured framework for the rapid identification of relevant articles dealing specifically with cognitive aspects in different systems. Such a choice is justified by the efficiency of searching in academic databases, where metadata is carefully selected and validated by authors and editors to reflect the core content of the article. Secondly, to mitigate the risk of not identifying relevant studies if the metadata is not complete, the current method has been supplemented by a manual check of the references cited in the articles initially identified, enabling the discovery of additional contributions that may not have been captured in the initial metadata-based search. Table 1 summarises the total number of articles obtained from each database per search string, providing an overview of the research outcomes. These articles have been then filtered according to the criteria explained in the following section.

2.1.3. Papers filtering

During the filtering process, selection criteria are utilised to identify primary studies that directly address the research questions, in accordance with the recommendations outlined in Kitchenham (2007-01-01). The inclusion and exclusion criteria are formulated based on the research objectives and are documented from the protocol definition stage to minimise the potential for bias.

Table 2
Exclusion and inclusion criteria.

E/I	Criteria
Exclusion	Duplicate papers
	Papers not accessible: a paper without full text to be assessed
	Papers written in other languages than English
	Entire conference proceedings
	Irrelevant primary studies
	Redundant paper from a same author: it refers to situations where an author publishes multiple papers on the same topic or with highly overlapping content
	Loosely related: articles that are not directly connected to the concept of cognition
Inclusion	Articles offering definitions
	Studies providing answers to the research questions
	Relevance papers: direct association with Cognition or featuring Cognition as a key element within systems

Table 3
Paper selection phase.

Phase	Total N° of papers
Total number of paper from digital libraries	1079
N° of papers after snowballing sampling	1096
N° of papers after exclusion based on the paper access, language and type of research	607
N° of papers after exclusion based on title, abstract and keywords	152
N° of papers after exclusion based on full text = N° of included papers	90

Upon gathering all potentially relevant articles, a two-phase filtering process is undertaken to assess their relevance. The first phase involves a thorough examination of the title, abstract, and keywords of each article to determine their initial suitability. From this evaluation, articles are eliminated based on the specified exclusion criteria. This was followed by a detailed examination of the full articles, enabling a more in-depth evaluation. Following this, articles are further screened according to the defined inclusion criteria. The Exclusion/inclusion criteria guiding this selection process are detailed in Table 2. The selected articles and their descriptive analysis are shown in the next Section 2.2.

2.2. Descriptive analysis of papers

The initial search revealed 1079 references from the digital libraries, and 17 papers based on the snowball sampling. We then applied filtering on the total of 1079 papers guided by a series of inclusion and exclusion criteria as described in Table 2. First we excluded those papers that are not accessible, not written in English and duplicates. Consequently the number of considered papers dropped to 607. Moving forward, we analysed the rest of the papers, considering their title, abstract and keywords. Thus, the number of considered papers dropped to 152. Moreover, after reading and analysing the full text of the remaining papers according to inclusion and exclusion criteria, we selected 90 of them. Once the papers are selected, we classify them by the year of publication, country and application areas. Table 3 shows the details of the selection phase.

The study encompasses papers published up to July 2023. The temporal distribution of these publications is depicted in Fig. 1. There was a period of relatively low activity from 1995 to 2007, followed by a gradual increase in publications from 2008 onwards. The number of articles fluctuated between 2011 and 2018, with no clear trend of constant growth. A significant peak is observed in 2022, indicating a renewed and robust interest in Cognitive Industrial Systems research in that year, suggesting an increase in the importance of the field.

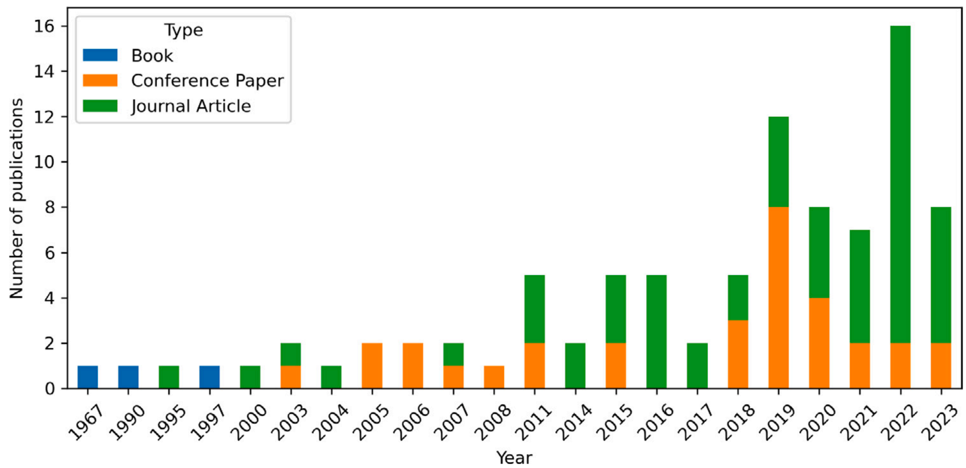

Fig. 1. Number of papers published per year.

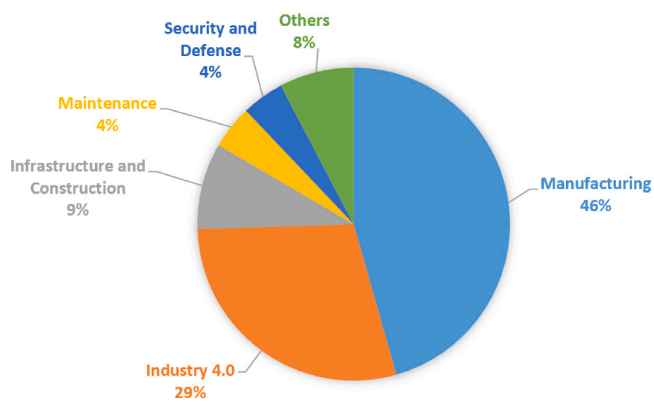

Fig. 2. Application areas of cognitive systems.

Our study targets industrial environments. However the analysed articles address cognitive systems for a diverse range of problems in multiple application areas. Fig. 2 shows the distribution among these. Without surprise, a big majority of articles concern Manufacturing and Industry 4.0. However it is interesting to see scores of some other areas. Infrastructure, referred to in our study as 'smart cities', shows a significant application of cognitive systems in urban management and optimisation. *Others* refers to the process industry, the chemical industry, the automotive industry and aerospace, and the cognitive enterprise thus bringing together a diversity of sectors that also have an impact in cognitive systems. For example Aerospace, although being at the origins of the Digital twin concept, seem to have a few interest for cognition. A few articles also refer to the Cognitive Enterprise but the concept seems only emerging.

In the following sections, we detail the answers to our search questions, starting with the foundations of cognition exploited in articles, thus covering our first four questions.

3. Theoretical foundations for systems' cognition

3.1. Cognition

In this section, we address RQ1: *How is cognition characterised and defined in the literature of cognitive psychology and human theories, and to which extent cognitive CPS and DT refer to it in their own perspective?* Cognition is a concept deeply rooted in cognitive psychology. It has been the subject of numerous studies and interpretations over the years and several authors have drawn on human cognitive theory to explore this notion. Ulric Neisser, often considered the father of cognitive psychology, was one of the first to lay the theoretical foundations of cognition. According to him (Neisser, 1967) the cognition refers to the mental processes by which individuals perceive, think, understand and interact with their environment. Central to these processes is the reception and interpretation of information (US, 1996), which, when effectively integrated through experiences, senses, and learning (Flower & Hayes, 1981), transforms into knowledge. This knowledge is not merely an aggregation of information but represents a profound synthesis that facilitates understanding, judgement, and decision-making (US, 1996). This process involves not only the acquisition but also the retention and utilisation of knowledge (Niu et al., 2009). Then, human theories of cognition were established. Allen Newell (Newell, 1990) brought the notion of cognition as a symbolic information processing system, a complex network where symbols are manipulated to produce thoughts and decisions. Marvin Minsky (Minsky, 1988) proposed a modular view with his *Society of Mind*, where mental agents interact to create an overall cognitive experience. Building on this foundational understanding of cognition, a diverse spectrum of paradigms has emerged (Pacaux-Lemoine et al., 2022), each offering unique perspectives on the intricacies and subtleties of cognitive processes. *Cognitive mimic* analyses human information processing to be mimicked by intelligent technologies (Karvonen & Saariluoma, 2023-01). *Cognitive science* is an interdisciplinary approach to understanding the mind that combines several different levels of analysis (Hozdić & Makovec, 2023; Ye et al., 2022). Derived from this field, cognitive heuristics have been identified, which can be thought of as mental shortcuts or models inspired by the way the human brain works. Cognitive heuristics are designed to facilitate the dissemination and interpretation of semantic data and associated data elements. Their design is inspired by the way humans store and process semantic information in memory (Mordacchini et al., 2016).

Cognition stands as the central pivot of the mental processes that enable us to interact with the world around us. It is shaped by intentional interactions between individuals and their environment, enabling the realisation of specific tasks and goals in a variety of contexts (Anttila et al., 2022-01-05). At a deeper level, it reflects our ability to acquire, process, store and understand information. This ranges from the simple absorption of knowledge to a deep and nuanced understanding of concepts (Angulo et al., 2023-04-01). The human brain, with its remarkable capacity to process an unlimited amount of information, is the key player in these cognitive processes. It enables us to understand, interact and respond to stimuli in our environment, demonstrating its complexity and flexibility (Zheng et al., 2017-01-16). This interaction with information is influenced by our previous experiences, our acquired knowledge, both procedural and declarative (Anderson, 1996;

Table 4
Comparative definitions.

Theme	Definition	CDT	CCPS
Awareness	Cognition can be defined as the integrative ability to perceive and understand the environment and social context, to learn from past actions, and to use this knowledge to reason, predict and optimise behaviours and decisions to achieve specific goals. It encompasses the real-time analysis and intentional awareness that informs problem-solving and work production.	Johansen et al. (2023), Kalaboukas et al. (2021)	Abie (2019-05-01), Al-Turjman (2017-02-01), Anttila et al. (2022-01-05)
Knowledge acquisition and understanding	Cognition is the action or mental process by which we acquire knowledge and understanding by mobilising thought, experience and the senses.	Johansen et al. (2023)	Angulo et al. (2023-04-01)
Information processing	Cognition, in the context of information processing, can be defined as the set of capacities and processes by which the human brain processes, understands and interacts with information from its environment. This includes the transformation, reduction, elaboration, storage, retrieval and use of sensory data.	Faruque et al. (2021), Kalaboukas et al. (2021), Mortlock et al. (2022), Neisser (1967), Yitmen et al. (2021)	Fischbach et al. (2020), Zheng et al. (2017-01-16)

Juarez-Espinosa, 2003), and even extends to the way other animals perceive and react to their environment (Castro & Andrade, 2018). Cognition is also a continuous exploration of knowledge, involving reflection, personal experience and sensory interaction. It is the mechanism by which we make sense of our world, encompassing everything from sensation and perception to more complex processes such as attention, learning, memory and language (Jones et al., 2006). Within the realm of *Cognitive Factory* (Colangelo et al., 2019), cognition is perceived as the capability of interpreting data, learning, and making decisions (Baum, 2004; Niu et al., 2009; Sternberg & Stemberg, 2012).

In industrial contexts, as represented by our articles set, it seems that cognition is considered from many angles, reflecting its multidimensional nature. In CCPS systems, cognition is largely conceptualised around interaction with the environment and decision-making based on these interactions, as demonstrated by the work of Al-Turjman (2017-02-01) and Abie (2019-05-01). This perspective focuses on real-time analysis, learning and decision-making. On the other hand, CDTs tend to focus more on how cognition relates to knowledge acquisition (Johansen et al., 2023). Interestingly, both CCPS and CDT integrate aspects related to information processing, as shown by Zheng et al. (2017-01-16) and Kalaboukas et al. (2021). The discussion also refers to important figures in cognitive psychology such as Neisser (1967), recognising the fundamental role of these ideas in understanding cognition within technology. Table 4 summarises the different definitions of cognition that could be found in our analysis. Generally, it is recognised as being an ability, involving processes qualified as 'mental'. We have grouped definitions according to the specific objective authors attach to cognition. Definitions under *Awareness* focus on the awareness of the environment, exploited for decision-making. *Knowledge acquisition and understanding* focuses on how knowledge is acquired, and finally *Information processing* relates to the processing of information or knowledge in general.

In conclusion, cognition goes beyond mere theoretical concepts or isolated functions; it includes a wide range of processes. In a modern context, particularly with the rise of Industry 4.0 (Faruque et al., 2021; Mortlock et al., 2022), cognition within industrial systems (CCPS and CDT) has become essential for processing and analysing vast volumes of data (Fischbach et al., 2020), offering solutions for use cases such as real-time monitoring, process optimisation and anomaly detection. Despite this statement, the use of cognition too often relies on a common understanding without referring to established research and definition from neurosciences or cognitive psychology. Without delving into the fundamental concept of cognition, many articles in this field directly address topics such as CCPS or CDT, topics which will be examined in more detail in the following sections. The following section presents the cognitive functions that support the integration of human cognition in these systems.

3.2. Cognitive functions

This section concerns RQ2: *Which cognitive functions are integrated into CPS and DT?* Cognitive function refers to mental processes involved in the acquisition of knowledge, manipulation of information, and reasoning (Kiely, 2014). These functions include various domains such as perception, memory, learning, attention, reasoning, decision making, problem-solving and language abilities (Vernon et al., 2007). There are several ways to conceptualise cognitive ability domains, including classification by the general process involved, such as memory or attention (Harvey, 2019-09). Some important cognitive skills include short-term memory, logic, processing speed, attention, and spatial recognition.[2] Classical models of human cognition have been conceptualised by cognitive scientists within an information processing paradigm, which is grounded by a computational metaphor that draws an analogy between mental operations with the functioning of a computer (Kiely, 2014). When systems like CPS or DT implement cognitive functions, they become cognitive systems, which has its own branch of research. Humans can already be qualified as cognitive systems, but machines or CPS/DT not yet. Cognitive systems are designed to simulate the functioning of the human brain (Abie, 2019-05-01). Particularly, they would be "*capable of human-like motivation, emotion, and personality, highly skilled and knowledgeable, and performing human-like reasoning and learning*". More generally, human-like characteristics in machines are expected to facilitate human–machine communication and mutual understanding, where humans can more easily interpret and predict machine behaviour. The similarities would allow humans and machines to socialise and establish a trust relation, thus allowing collaboration and partnership.

Research on CCPS and DT are a first step towards transforming CPS and DT into cognitive systems. The literature shows that cognitive functions can be implemented in CCPS and CDT to enable them to learn, reason, and make decisions. However not necessarily the same functions have been considered in the articles. Fig. 3 shows the cognitive functions referred in the articles and their frequency of appearance for CCPS and CDT.

In the context of CCPS, *reasoning* (Angulo et al., 2023-04-01; Colangelo et al., 2019; Dumitrache et al., 2019; Jiang et al., 2022; John et al., 2021) is essential for processing information, drawing conclusions and making decisions based on logic and understanding. *Attention* and *perception* (Angulo et al., 2023-04-01; Colangelo et al., 2019; Dumitrache et al., 2019; Jiang et al., 2022; John et al., 2021; Oliveira et al., 2019) in these systems is often focused on grouping and retrieving data, taking into account the limited processing capacity and large amount of data from environmental inputs. *Situational awareness* (Abie, 2019-05-01)

[2] https://www.verywellmind.com/what-is-cognition-2794982

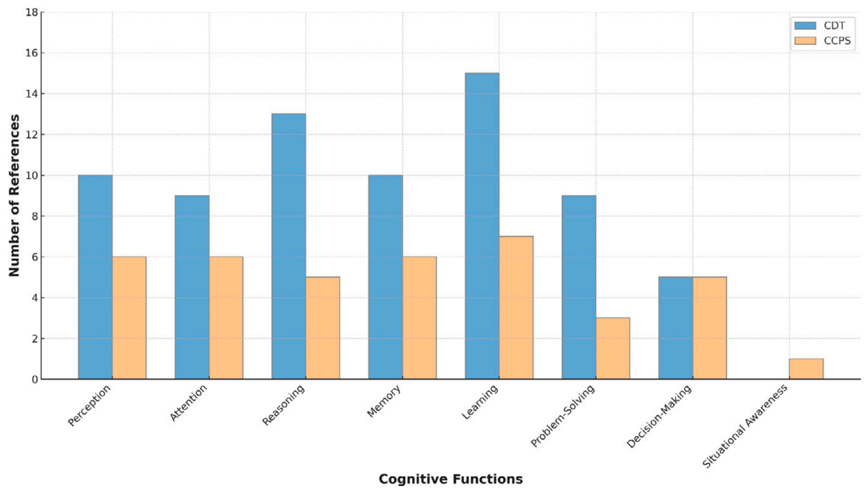

Fig. 3. Comparison of cognitive functions in CDT and CCPS.

is also crucial, as it enables these systems to adapt to environmental changes, ensuring optimum safety and adaptability. In the literature, other cognitive functions such as *learning* (Bocklisch et al., 2022-04-01; Colangelo et al., 2019; Dumitrache et al., 2019; Jiang et al., 2022; John et al., 2021; Oliveira et al., 2019; Topal et al., 2020), *decision-making* (Jiang et al., 2022; John et al., 2021; Mizanoor Rahman, 2019; Oliveira et al., 2019), *problem solving* (Bocklisch et al., 2022-04-01; Jiang et al., 2022; John et al., 2021) and *memory* (Angulo et al., 2023-04-01; Bocklisch et al., 2022-04-01; Dumitrache et al., 2019; Jiang et al., 2022; John et al., 2021; Topal et al., 2020) have been represented to define a CCPS. In the context of CDT, cognitive functions have been used by various authors (Abburu et al., 2020a, 2020b; D'Amico et al., 2022; Eirinakis et al., 2022; Enrique & Soares, 2022; Faruque et al., 2021; Intizar Ali et al., 2021; Jinzhi et al., 2022; Johansen et al., 2023; Kalaboukas et al., 2021; Mokhtari et al., 2022; Mortlock et al., 2022; Yitmen et al., 2021; Zhang et al., 2020; Zheng et al., 2022). Faruque et al. (2021) have distinguished and defined the cognitive functions of a Digital Twin as follows: *Perception* concerns the way in which these systems transform data representations into useful information. *Attention* describes the process by which they selectively focus on certain tasks or data, eliminating superfluous or distracting elements. *Reasoning* enables them to draw conclusions in accordance with a starting point or perception, often based on a pre-existing memory or set of assertions. *Learning* is the process by which they transform experience into reusable knowledge, enabling them to adapt and evolve in response to new information. *Problem-solving* and *decision-making* are closely linked, enabling the digital twin to find solutions to challenges or achieve specific goals. Finally, *memory* is a central element enabling them to retain and recall information, be it memories of specific events or general knowledge about their environment. The graph shows notable distinctions in the cognitive functions associated with CCPS and CDT systems. These discrepancies stem from the divergent evolution of the two technologies; CCPS, which merge the digital and the physical, may focus on real-time interaction with their environment, hence a priority for situational awareness. On the other hand, CDT, digitally representing real processes, could be focused on simulation and prediction, emphasising perception and reasoning. This divergence also reflects current research trends, the technological challenges specific to each system, or the inherent complexity of each type of system. Improved cognitive abilities would enable better integration of domain-specific knowledge and provide better clues for real-time decision-making (Rožanec et al., 2022). In Abburu et al. (2020a), the authors highlight that cognition functions enable understanding: they make sense out of data under uncertainties, generating knowledge that supports reliable decision-making or control. They formalise the cognition process as: inserting new knowledge (Dhakal & Bobrin, 2023), learning new models, better situational understanding, and action planning. This leads to challenges related to knowledge representation, acquisition and update, which are in fact classical ones in knowledge engineering.

The two following sections detail the technologies that are exploited in papers to implement cognitive functions. The second section highlights two specific enabling technologies: *Cognitive Computing* and *Cognitive Architectures*.

3.3. Supporting technologies

This section addresses RQ3: *What particular methods, strategies or models are used to implement cognition in CPS and DT?* The integration of cognition into industrial systems focuses on the intersection of AI and cognitive technologies (Elia & Margherita, 2022; Enrique & Soares, 2022). Although the two are different, they are frequently used indiscriminately, as they both aim to replicate human intelligence. Cognitive technologies focus on specific areas of human cognition, such as language and vision, while AI includes a broader spectrum of technologies and applications. A simple way of distinguishing these two technologies would be to consider cognitive technologies as a sub-category of the AI technology set (Hozdić & Makovec, 2023). In the field of cognitive Cyber–physical systems (CCPS), various AI techniques can be classified according to their specialised functions. Analysis and reasoning capabilities are fundamental, with contextual and behavioural analysis enabling data to be understood in its situational context, and logical reasoning algorithms facilitating complex decision-making. Added to this are predictive analyses, such as regression algorithms, which anticipate future scenarios, reflecting the ability of human cognition to anticipate (Abie, 2019-05-01). The field of natural language processing (NLP) contributes to the contextual dynamism of AI, with applications ranging from conversational agents, such as chatbots, to machine translation, a linguistically challenging task (Hozdić & Makovec, 2023). As a new field derived from NLP, Large Language Models (LLM) certainly open new perspectives for cognitive systems, giving them the ability to extract knowledge directly from human language, ultimately understanding it, to learn, and to interact with humans in their own language. By incorporating cognitive functions into CPS, LLMs can adapt dynamically to new situations, overcoming the limitations of traditional AI method (Hozdić & Makovec, 2023). Computer vision, another fundamental element of AI, is particularly effective in the field of facial recognition using Machine Learning (ML) and Deep Learning (DL) algorithms, enabling systems to interpret and understand visual information in a way that closely resembles human perception (Hozdić & Makovec, 2023). A more specialised but equally revolutionary technology is eye-tracking, which precisely measures and analyses eye activity, offering a nuanced insight into how individuals interact visually with their environment (Bocklisch et al., 2022-04-01).

On the other hand, CDT cover a complex set of technologies designed to mimic human cognitive processes. At the forefront of text analysis is the field of NLP, which comprises a wide range of techniques for interpreting and generating human language. Among the algorithms used by NLP and DL are Long Term Memory Networks (LSTM) (Lv et al., 2023); although very much present in NLP for their ability to process sequential data, LSTM networks are versatile tools that are equally applicable to a whole range of other fields, including time series analysis. Within the sphere of visual processing, computer vision is a distinct field, employing DL technologies such as the VGG network to master image recognition and analysis (Lv et al., 2023). The integration of these technologies illustrates the sector's specialisation and its essential role in understanding visual content. The work cited in Asadi (2022-01-20) introduces an innovative approach with Memory pool, an improved memory allocation system that secures the processing of user data. In addition, machine learning methodologies are extending their influence to cognitive simulation (Asadi, 2022-01-20; Eirinakis et al., 2020; Mokhtari et al., 2022; Mortlock et al., 2022), as illustrated by graphical learning, which optimises device functionality and simulates cognitive operations (Kalaboukas et al., 2021).

In synthesising the analysis, the integration of AI and cognitive technologies represents a synergistic approach to mimicking human intelligence, combining the specificity of cognitive technologies in areas such as language and vision with the broad technological spectrum of AI. This collaboration forms the bases of advances in CCPS and CDT, which draw on a diverse set of techniques ranging from predictive analytics to natural language processing and computer vision. These technologies not only improve our understanding of data in context, but also pave the way for the simulation of complex cognitive functions, advancing the field towards more nuanced, human-like interactions with digital systems.

3.4. Cognitive computing and cognitive architectures

In this section, we address RQ4: *What are the theoretical foundations of cognition used in CPS and DT, and how do they help to implement the cognitive processes?*

Cognitive computing and *Cognitive architectures* are enabling technologies for building cognitive systems. Cognitive Computing was presented as the next generation AI by IBM, as "*a computing paradigm where computing systems are no more deterministic, following their programming rules, but rather probabilistic, by learning, reasoning and adapting to a changing environment*", to enhance the perception, reasoning and decision-making capabilities of computers (Zheng et al., 2017-01-16). It materialises the concept of embodied cognition,[3] which refers to embedding cognition capabilities in some (physical or virtual) entity with which humans can interact naturally. The focus is given on the ability of agents to become cognitive systems, i.e., able to "observe, recognise and identify" and able to *learn* and *improve themselves*, *to negotiate* in their interactions, and even *capable of empathy* (Sathi, 2016). The cognitive computing framework comprises six interdependent cognitive components: comprehension, verification, planning, evaluation, attention and perception. According to Zheng et al. (2017-01-16), each of these components can serve as a starting point or goal in a specific cognitive task. The system chooses an interactive path, simple or complex, to reach the cognitive goal, depending on the information needed to interact with the outside world.

The study of systems capable of learning and reasoning has led to the development of general cognitive architectures, which are essential for the design of entities capable of emulating the complexity of the human mind for computational implementation. Universal theories of cognition, such as ACT-R (Anderson, 1996), Soar (Newell, 1990), ICARUS, LIDA and others reported in Vernon et al. (2007), illustrate this approach by attempting to integrate all cognitive processes and interactions. These models draw on foundations in psychology, cognitive science and neuroscience to create systems that not only simulate, but also aim to understand the intrinsic nature of human cognition. These architectures, which have been around for some time, continue to be key references in cognitive research, underlining the importance of such integrative approaches to progress in the understanding and reproduction of human cognition by machines. The ACT-R theory, developed by Anderson, postulates that cognition emerges from the collection and adjustment of many small pieces of knowledge. In practice, ACT-R serves as a framework for cognitive modelling and enables the integration of complex models within distributed systems, thus improving the integration of these models into larger systems (Bunte et al., 2019; Sycara et al., 2015). Newell, through his Unified Theories of Cognition (Newell, 1990), emphasised the integration of various cognitive processes within a single unified system, suggesting that global understanding of cognition can be achieved by combining its various components. He also developed the Soar architecture, a candidate for his theory, which uses a bipartite memory system, with long-term and working memory. It works state by state, defining problem spaces and operators, and uses a deadlock trial-and-error mechanism to generate new rules that prevent future obstacles (Bunte et al., 2019; Mittal & Douglass, 2011). Next, ICARUS follows in the tradition of cited architectures, engaging in a specific way of representing knowledge, inferring beliefs, executing and learning new knowledge (Choi & Ohlsson, 2011). Also included is the LIDA model, which is designed to simulate the cognitive functions of an autonomous agent, covering processes like perception, attention, memory, and decision-making, in alignment with theories of embodied and situated cognition (Lv et al., 2023). It operates on a cycle of perceiving sensory inputs, which then inform attention mechanisms, learning, and subsequent actions that affect the environment. This involves multiple memory systems for storing information and mechanisms for learning and action selection (Franklin et al., 2016). While the LIDA framework has been applied in practical software agents and neuroscience simulations, it represents one of the many complex cognitive architectures that strive to closely mimic human cognition. Research in this field is vast and ongoing, but architectures like LIDA are essential for creating more intelligent, interoperable cognitive systems, which are discussed in the next section. More precisely, we address there our questions RQ5, RQ6 and RQ7, learning about cognitive CPS, DT and interoperability, as well as the special role of KRR.

4. Cognitive systems in CPE

Built on cognitive systems, our current technological environment is moving rapidly towards integrating cognitive features. The discussions around Industry 4.0 emphasise the importance of taking care of large amounts of data (Fischbach et al., 2020), which include improving decision-making processes, and enabling facilitating adaptation within cognitive manufacturing (Dumitrache et al., 2019). Together, these elements work towards the realisation of a cognitive enterprise (Elia & Margherita, 2022), which extends beyond data analysis to the embodiment of cognition in technology. The increasing reference to terms such as CCPS, and CDT in the glossary of Industry 4.0/5.0 highlight this "cognitive" trajectory. We will explore three pivotal concepts that respond to the concluding research questions: firstly, the definitions of CCPS and CDT, which are central to understanding the cognitive underpinnings of these systems. Secondly, we will delve into the significance of cognitive interoperability, a critical aspect for seamless integration across diverse cognitive frameworks. And finally, we will discuss how KRR supports cognition and facilitate this interoperability in such systems. In the following each of these four topics is summarised according to the analysed literature, leaving the conclusions to draw from these summaries and related discussion to Section 5.

[3] Grady Booch, presentation given to IBM's Academy of Technology, March 23, 2016.

Table 5
Characterisation of CCPS in the literature.

Characteristic	Definition	References
Autonomous agents	A CCPS is an integrated, decentralised system that combines cognitive capabilities with the structure of a CPS. It is designed to function as an autonomous agent, capable of behaving and making decisions independently, without human intervention.	Fournaris et al. (2020), Mizanoor Rahman (2019), Oliveira et al. (2021, 2019)
Adaptability	CCPS is a CPS with cognitive abilities, capable of adapting their actions according to sensory information and uncertainty management.	Krueger et al. (2016)
Awareness	CCPS is a system that holds an advanced understanding of its environment and human interactions.	Al-Turjman (2017-02-01)

4.1. Cognitive cyber–physical systems

This section addresses RQ5: *How are cognitive CPS conceptualised, implemented, and applied within the context of Industry 4.0?* One of the primary technologies of Industry 4.0 is the CPS, which bridges the gap between virtual domains and the real world. This is achieved through the fusion of networking, computation, and storage capabilities, paving the way for interactive industrial settings and the emergence of Smart Factories (Carvalho et al., 2018-01-01). In essence, CPS are automated, distributed frameworks that seamlessly combine physical existence with communication systems and computing platforms (Wang et al., 2015). The CCPS concept is relatively new. According to Zhou et al. (2019), the task of cognition in CCPS is to efficiently acquire the knowledge necessary for the system to achieve its objectives; this task is essential for effective decision-making and control. Khargonekar (2019) presents a vision for it, where it is defined as a CPS that has cognitive functions and capabilities. Those can be programmed by design or be learned from interactions with other CCPS and humans. Table 5 presents the CCPS definitions extracted from our study, organised according to their specific application as identified in the publications. CCPS integrates multiple facets that combine intelligence with physical processes, categorised into three distinct yet interrelated aspects. *Adaptability* emphasises the ability of the CCPS to change and optimise its behaviour in response to changing environments and internal dynamics. *Autonomous agents* refers to the ability of CCPS to self-monitor and solve problems. Finally, *Awareness* focuses on the system's perception of its environment and its own state. All CCPS systems have a detailed set of characteristics; however, in the literature, studies are generally organised according to the specific characteristic they are examining, such as adaptability, autonomy or awareness.

According to the definitions found in the literature, CCPS are identified as entities capable of autonomy, adaptability and environmental awareness. These systems are designed to operate without human intervention, dynamically adjust to changes in their environment using their cognitive capabilities, and have a deep understanding of their operational context. In Oliveira et al. (2019) these systems are capable of detecting and analysing the environment, and then making decisions based on the results of this analysis. This aspect of CCPS is examined in more detail in Mizanoor Rahman (2019), where the focus is on building mutual trust in human–robot collaborations. CCPS in Fournaris et al. (2020) are designed to be holistic, decentralised and cognitive. They enable cyber–physical system-of-systems (CP-SoS) to operate autonomously, without human intervention. From another perspective, robots with cognitive capabilities are able to adapt their actions based on sensory information and uncertainty management, as mentioned in Krueger et al. (2016). More recently, Oliveira et al. (2021) presents it as an autonomous cooperative system of CPS with a cognitive architecture enabled by AI, which can interact deeply with a physical system. Cognition here is a tool to move from controlled to autonomous systems that do not necessitate human intervention. It also enables the CCPS to have the ability to be aware of the environment and human interactions, to learn from past actions and use them to make future decisions that benefit the network (Al-Turjman, 2017-02-01). According to Zhou et al. (2019), the task of cognition is to efficiently acquire the knowledge necessary for the system to achieve its objectives; this task is essential for effective decision-making and control. In addition to these definitions, another way in which CCPS has been presented is through the integration of cognitive radios with CPS, which trains cognitive abilities to obtain information about transmission requirements or spectrum availability in order to improve performance (Topal et al., 2020). This section covers various methods of analysing cognition in CPS, our own analysis and definition based on this research is discussed in Section 5.

4.2. Cognitive Digital Twin

This section deals with RQ6: *How are cognitive DT conceptualised, implemented, and applied within the context of Industry 4.0?* A DT is a holistic digital and virtual engineering model of a product or more generally a system. Different tools and technologies are available for developing high-fidelity virtual models (Schleich et al., 2017). Various methods are used to create very detailed models (McGregor, 2002), such as simulation, which predicts system behaviour (Law & Kelton, 2000), and emulation, which mimics it in real-time (Ayani et al., 2018). Simulation provides a broad and fixed overview of the system, while emulation is a dynamic, live replica that acts like the actual system (Semeraro et al., 2021). The use of digital twins is often limited to an exact replica of physical assets, without any cognitive capacity (Intizar Ali et al., 2021). The concept of CDT was introduced to designate Digital Twins that are extended with AI processes and functions giving them reasoning, decision-making and autonomous acting capabilities. Our analysis revealed that ways of defining CDT vary from one research work to another. Table 6 presents a consolidated view of CDT definitions from our research. CDT integrate multiple facets of intelligence and digital twinning, categorised into four distinct yet interrelated aspects. *Semantic Modelling* pertains to the CDT capability to create detailed and interpretable models that mirror physical entities. *Autonomous Agents* emphasises the self-sufficient operation of CDTs, enabling them to act independently. *Real-Time Reasoning and Decision* focuses on the CDT ability to process data and make decisions swiftly, impacting immediate actions. Lastly, *Adaptability* refers to the CDT capacity to evolve by learning from new data and adapting to changes. All CDTs include detailed features, however, references are grouped based on the specific aspect each study focuses on.

What we could observe in the state of the art is that semantic modelling seem crucial for understanding the evolution of virtual models and improving decision-making, thus reflecting the importance of understandably in complex system interactions (D'Amico et al., 2022; Kalaboukas et al., 2021; Li et al., 2022; Lu et al., 2020). Next, the inclusion of autonomous agents indicates that CDTs are not static; they are capable of real-time reasoning and autonomous problem solving, which is fundamental for applications where operational independence is paramount (Asadi, 2022-01-20; Mokhtari et al., 2022; Yitmen et al., 2021). Additionally, real-time reasoning and decision-making ability is highlighted as an advanced attribute, indicating that CDTs operate with contextual awareness and immediate responsiveness (Eirinakis et al., 2020; Intizar Ali et al., 2021; Mokhtari et al., 2022; Zhang et al., 2020). Ultimately, adaptability highlights the CDT ability to evolve

Table 6
Characterisation of CDT in the literature.

Characteristic	Definition	References
Semantic modelling	A DT with augmented semantic capabilities for identifying the dynamics of virtual model evolution, promoting the understanding of interrelationships between virtual models and enhancing the decision-making based on DT	D'Amico et al. (2022), Kalaboukas et al. (2021), Li et al. (2022), Lu et al. (2020)
Autonomous agents	A DT that uses real-time reasoning and problem-solving skills to interpret information and make autonomous decisions. This system is adept at using its cognitive abilities to control processes, react to unexpected events, and handle unknown situations independently, without human intervention.	Asadi (2022-01-20), Mokhtari et al. (2022), Yitmen et al. (2021)
Real-Time Reasoning and Decision	An advanced evolution of DT, with the ability to reason, interpret and act in real time. It integrates enhanced communication, analytical and cognitive capabilities, enabling decision-making and process control based on accurate observations, in-depth knowledge and experience.	Eirinakis et al. (2020), Intizar Ali et al. (2021), Mokhtari et al. (2022), Zhang et al. (2020)
Adaptability	A DT composed of interlinked digital models that reflect various lifecycle stages of the physical counterpart, including all subsystems and components. Notably, it has the distinctive ability to continuously evolve in parallel with the physical system throughout its entire life-cycle.	Abburu et al. (2020b), Jinzhi et al. (2022), Zheng et al. (2022)

in parallel with its physical counterpart throughout the life cycle, suggesting intrinsic flexibility and continuous evolution (Abburu et al., 2020b; Jinzhi et al., 2022; Zheng et al., 2022). Dividing references according to the specific mode of application in each paper indicates that, although each CDT may possess all of these characteristics, studies often focus on one or more specific features in particular application contexts. This reveals the breadth of application areas of CDTs and the diversity of research approaches, while confirming the interdependence of different characteristics to realise the full potential of CDTs.

Building on this, cognition is understood as the ability to understand context, reason on top of existing information, predict and optimise behaviour, and the CDT model integrates services supporting each of these. CDT is presented as a necessary enabler for agile supply chains, fulfilling the need for synchronisation, knowledge sharing, responsiveness, and optimisation across the potentially complex network of actors. Thanks to its cognitive features, the CDT is expected to be able to detect different types of behaviours of the physical twin, for any combination of predictable and desired status, and predict impacts. These additional capabilities make CDT an autonomous intelligent agent as defined in AI (Maes, 1995; Sabharwal & Selman, 2011) and Agent-Based Computing (ABC) (Luck et al., 2004) fields. The CDT model, or profile in Kalaboukas et al. (2021), is implemented as an ontological knowledge graph associated to status, behaviour, specifications, processes the DT is part of as well as API and optimisation services supporting the cognition process. Another approach was considered by Abburu et al. (2020b) which considered three progressive levels of cognitive augmentation for DT: Digital Twin, corresponding to the classical digital replica where isolated models of the physical twinned are created; Hybrid DT, where the models are interrelated allowing some prediction; and finally Cognitive DT, which has knowledge manipulation and problem-solving capabilities allowing to deal with unknown situations. The cognitive capabilities of the CDT include sensing, reasoning and self-learning, leading to continuous adaptation of structure and behaviour, and thus proactively. This section covers various methods of analysing cognition in DT, our own analysis and definition based on this research is discussed in Section 5.

4.3. Interoperability and cognitive systems

This section addresses RQ7: *How can interoperability within industrial environments be enhanced by cognition, and is there a concept of cognitive interoperability?* Interoperability aims to enable different systems or components to work together seamlessly, sharing data and functionality without hindrance. The key to achieving this lies not only in technical solutions, but also in understanding and aligning with human behaviours, communication patterns and thought processes, hence the need for cognitive interoperability. The concept first appeared in the military sector (Klose et al., 2005), with the development of a collaborative command and control portal. This initiative highlighted the importance of aligning system operations with human cognitive capabilities to improve decision-making and operational efficiency. Cognitive interoperability, as illustrated in the context of the C4ISR (command, control, communications, computers, intelligence, surveillance and reconnaissance) model (Blad & Potts, 2003), focuses on the need for shared understanding and unity of effort between team members. It focuses on the mental processes involved in decision-making, including perception, awareness, understanding and the integration of beliefs and values. It refers to a unity of mindsets, confidence/trust and mutual understanding based on shared education and values. It is understood as a human function and "*a state of mind that sets the foundation for cooperative and effective action*".[4] In the nearby domain of crisis management, Kwon et al. (2011) studies the socio-cognitive aspects of interoperability to support communication and joint decision-making among multiple safety organisations. Those aspects concern the impact of human factors on all interoperability dimensions with issues faced by humans in this particular context, which have to be taken into account to improve communication and decision-making.

Referring to technical (IS) interoperability in e-government, Cognitive Interoperability in Goldkuhl (2008) is a part of organisational interoperability related to the "*congruence in thought and perceptions*" or "*the human actors' way of thinking*".

In Geographic Information Systems, Raubal (2005) introduces Cognitive Semantic interoperability, arguing that semantic interoperability should build on the theories of cognitive semantics and human spatial cognition. This highlights that when sharing knowledge, because the meaning of terms are in people's heads, the mental models of both the sender and the receiver have to be mapped for a complete understanding.

In the human–machine interaction research field, Semiotico-Cognitive Interoperability is presented in Berthier (2006) as the link AI seeks to establish between human and machine. The term semiotico-cognitive interoperability is used especially for man-machine communication, where an artificial agent "*appears to behave in the same way as a human agent would in the same situation and, in particular, that (to a predefined extent) some meanings seem to be shared between the user and the agent*". This interoperability is limited here to virtual agent-to-agent communication using standardised languages and normalised means to translate between different knowledge representations, including ontologies. Cognitive interoperability is also referred at several levels in Krinkin and Shichkina (2023): between the developer and the intelligent system created, between human and machine intelligent agents within a hybrid system, and between different intelligent systems. This interoperability enables effective collaboration, whether to work

[4] https://www.academia.edu/28803917/Cognitive_Interoperability_

Table 7
Number of references for each category and domain.

	CDT	CCPS
KG	Asadi (2022-01-20), D'Amico et al. (2022), Eirinakis et al. (2020, 2022), Intizar Ali et al. (2021), Jinzhi et al. (2022), Johansen et al. (2023), Kalaboukas et al. (2021), Lv et al. (2023), Mokhtari et al. (2022)	Dourlens and Ramdane-Cherif (2011), Iarovyi et al. (2015), Liu et al. (2022)
Ontologies	D'Amico et al. (2022), Eirinakis et al. (2020), Intizar Ali et al. (2021), Jinzhi et al. (2022), Kalaboukas et al. (2021), Li et al. (2022), Mokhtari et al. (2022)	Abie (2019-05-01), Castro and Andrade (2018), Dourlens and Ramdane-Cherif (2011), Iarovyi et al. (2015), Liu et al. (2022)

within a common knowledge ontology, jointly extract new knowledge or cooperate between independently created systems.

While the term cognitive interoperability may not be extensively explored in literature, there are studies that examine how cognitive systems can interact and operate coherently and efficiently. Jinzhi et al. (2022) highlights the need for data interoperability to take full advantage of CDT, highlighting initiatives such as Open Collaboration Throughout the Lifecycle (OSLC) that facilitate data exchange and exploitation. Furthermore, Krueger (Krueger et al., 2016) highlighted how the organisation and clarification of information, both semantically and metrically, significantly facilitates the interaction and understanding of data between different cognitive systems. On the other hand, Liu et al. (2022) propose a two-pronged strategy to increase interoperability between cognitive systems. They distinguish between a part devoted to immediate perception and reactive, data-driven decisions, and a second oriented towards more in-depth, structured cognitive reasoning. This methodology, while not explicitly using the term "cognitive interoperability" certainly captures its essence through the blending of real-time data perception and cognitive reasoning, enabling quick and well-informed decisions. These studies provide insights into the possibilities of interoperability among advanced cognitive systems, illustrating how such interoperability can be realised in industrial contexts.

The research discussed in this section allows us to conclude with insights into the realisation of cognitive coupling between operating agents within a larger system, which will be discussed further in Section 5. Next, the following section explores the use of KRR as an important and maybe essential tool for cognitive processes and interoperability in CPSS and CDT.

4.4. KRR for cognitive systems and interoperability

This section addresses RQ8: *What types of knowledge representation and reasoning approaches are commonly used in CPS and DT to structure and manage relevant knowledge for specific cognitive tasks, and facilitate cognitive interoperability?* An important aspect of cognition lies in the elaboration of knowledge, which plays a key role in analysing changes in processes, especially when it comes to identifying and interpreting unexpected variations (Johansen et al., 2023). Knowledge Representation and Reasoning, which belongs to the symbolic kind of AI, becomes a fundamental tool for conceptualising cognition across diverse systems and for introducing cognitive interoperability between these systems. In this context, ontologies and Knowledge Graphs (KG) emerge as key components of KRR, providing effective means for structuring and manipulating information. Table 7 illustrates the studies that have implemented these instruments in the context of CCPS and CDT.

According to all the references in Table 7, ontologies enable seamless communication between systems and also enrich semantic reasoning, indicating a move towards cognitive capabilities. At the same time, KGs help to analyse and inform the decision-making processes of these systems. They evolve to become dynamic and underlie continuous learning, thus contributing to autonomous reasoning capabilities. In Oliveira et al. (2019), authors suggest that CCPSs rely on the concept of decision DNA (DDNA) to store and share knowledge gained from decision-making experiences, thus supporting the cognitive development of the system. On the DT side, CDTs can combine quantitative (such as ML and data analysis) and qualitative (such as KG) data-driven approaches to refine results and improve processing and reasoning capabilities (Eirinakis et al., 2020). We conclude here that KRR technologies support the emergence of cognitive systems (CCPS and CDT) capable of transforming raw information into knowledge objects, and refining this knowledge in the same way as the human process of acquiring and evaluating information.

KRR plays an important role in achieving cognitive interoperability. They integrate semantic web tools, notably the Resource Description Framework (RDF), to create a common semantic base, facilitating uniform interpretation and processing of information by different systems (D'Amico et al., 2022). They ensure that systems can communicate fluidly, sharing and understanding data consistently. In addition, graphical representations, which combine spatial and semantic data, enhance this communication by linking various forms of knowledge (Krueger et al., 2016). Furthermore, these articles (Krinkin & Shichkina, 2023; Kwon et al., 2011) explain the need for systems integrating both social and cognitive capabilities for true socio-cognitive interoperability between systems and their human users.

5. Analysis and results

Following our systematic review of the literature on cognitive systems in the industrial context, we refine our theoretical understanding here. Definitions have been developed for cognitive systems in general, as well as for cognitive cyber–physical systems and cognitive digital twins.

5.1. Foundations

The limitations observed in the performance of CPS and CDT underline the need to get a better understanding of the complex aspects of human cognition. This understanding is essential for efficiently integrating cognitive processes into technological systems. In cognitive psychology, Neisser's description of cognition as the transformation and use of sensory data provides insight into the complexity of human cognitive processes (Neisser, 1967). Although other influential models exist, such as Newell's *unified theories of cognition* (Newell, 1990) and Minsky's *Society of Mind* (Minsky, 1988), Neisser's process-oriented approach offers a continuous and dynamic perspective, as it emphasises the fluidity and adaptability of human cognition. Thus, *cognition goes beyond mere data collection; it concerns the transformation, storage and effective use of knowledge to understand, judge and decide*. This view is central to cognitive science, which is a field that blends many disciplines, emphasising the depth and complexity of cognition itself (Hozdić & Makovec, 2023). Each discipline brings a unique method and perspective, enriching the overall analysis of cognitive processes or functions which are mental processes involving the acquisition, processing, storage and use of knowledge. According to Section 3.2, cognitive functions include various abilities such as *perception*, *attention*, *memory*, *problem-solving*, *reasoning*, *memory* and *learning*. We have seen that incorporating these functions into systems using AI and semantic modelling is a possible approach to simulate human cognitive capabilities, but it also would require some specific structuring that cognitive architectures could bring, to better humans in their way of thinking or processing information.

To improve cognitive functions in CCPS and CDT and make them closer from the ones of humans, we need tools or technologies that enable machines to act in a way that seems "intelligent" or that reproduces certain human capabilities. Our analysis has highlighted the use of AI at different levels for supporting cognitive functions. The two kinds of AI have been exploited: sub-symbolic with Natural Language Processing (NLP) (Hozdić & Makovec, 2023), Deep Learning (DL) and neural networks (Lv et al., 2023), and symbolic with KRR and ontologies. NLP and DL have seen rapid growth and application, given its pattern recognition and predictive capabilities based on intensive data training. Among the relevant technologies, NLP (Hozdić & Makovec, 2023) and Large Language Models (LLMs) are highlighted for their potential to enrich cognition in CCPS, even though no identified studies have yet implemented LLMs. Recurrent neural networks, such as LSTMs, are recognised for their effectiveness in sequential data processing (Lv et al., 2023). Computer vision and more advanced DL technologies such as eye-tracking are also notable for their contribution to the interpretation of visual data (Bocklisch et al., 2022-04-01). In this way, AI and cognitive technologies are essential for reproducing aspects of human intelligence such as language, vision and the ability to anticipate.

Current research on hybrid AI together with our current study suggests that implementing cognitive functions requires a seamless integration of symbolic AI and sub-symbolic AI (Zheng et al., 2017). Symbolic AI, with knowledge graphs (Ontology) and KRR, contributes to deep knowledge modelling, which is crucial for interpreting complex data and enabling autonomous decision-making. It structures and formalises knowledge, promoting semantic interoperability and advanced reasoning, which is fundamental in cognitive systems for simulating higher-order cognitive functions (Section 4.4). But for technological systems truly mimicking the cognitive capabilities of the human brain and achieving human-like cognition, it requires the integration of hybrid AI approaches within cognitive architectures. More specifically, architectures such as LIDA and SOAR do not just simulate intelligence; they strive to encompass the whole of human cognition, facilitating a rapprochement with human reasoning and decision-making processes (Franklin et al., 2016; Vernon et al., 2007). However, they are themselves complex systems, like the phenomena they model, and research in this field is still ongoing after more than twenty-five years. But LIDA or other architectures are certainly interesting candidates for giving cognitive things a "brain", taking a step towards systems and cognitive interoperability. By integrating knowledge graphs and ontologies with NLP/DL into these cognitive architectures, we are linking the ability to learn from data with the ability to reason in a complex, structured way, while processing information the same way human do. This combination contributes to deep knowledge modelling, which is crucial for interpreting complex data and enabling autonomous decision-making (Yu et al., 2023).

5.2. Definitions

Taking into account the results presented above, we have extracted a set of characteristics of cognitive systems. Cognitive systems in industry are complex systems, as they are made up of numerous elements that can interact with each other. So, first of all, the wide use of the word *system* in definitions found in the literature highlights the necessity to come back to the roots by considering a systemic view. According to the fundamental work of Von Bertalanffy (1972), the founders of general systems theory (GST), a system is before all *a complex set of interacting elements, whose properties are richer than the sum of its parts*.

Current research shows that cognitive systems are designed to mimic the human brain, enabling them to observe, adapt and improve autonomously. The aim is not to replace humans, but to work in symbiotic collaboration with them, based on the paradigm of human–computer symbiosis (Vermesan et al., 2022). These systems are capable of simulating human aspects such as motivation, emotion and personality, making their learning and actions comparable to those of human beings (Abie, 2019-05-01). Cognitive systems are at the core of technological interactions in the industrial field, enabling the execution of complex tasks and the comprehension of varied information (Angulo et al., 2023-04-01). They are equipped with cognitive functions that simulate human mental processes such as perception, memory, learning, attention, reasoning, decision-making and problem-solving (Kiely, 2014; Vernon et al., 2007). With these functions, cognitive systems can process sensory information, learn and reason in a structured way, simulating human cognition. This capacity for autonomous learning and adaptation is crucial for meeting specific needs in complex environments. In conclusion, cognitive systems aim to establish a close, symbiotic collaboration with humans, continually adapting and improving. They use AI with ontologies and knowledge graphs to simulate the functioning of the human brain. Thus, we propose the following definition, which integrates the capabilities of cognitive systems, while explicitly giving a systems perspective where cognitive systems inherit properties from systems:

Definition 1. A cognitive system is a system that integrates cognitive functions inspired by the functioning of the human brain, capable of learning, reasoning and decision-making. They can interact naturally with humans and continuously improve through their ability to adapt. These systems process and understand complex information, making it easier to solve a variety of problems and carry out complex tasks.

The Cognitive Cyber–Physical System (CCPS) is the next evolution of CPS. It adds a new dimension to traditional CPS, where it is given the ability to integrate and assimilate cognitive functions, either at the design stage or through interactions with its environment. This integration results in autonomy, highlighting the system's ability to self-manage, learn from its environment and make decisions autonomously, aligning with human perspectives of intelligence and reactivity (Khargonekar, 2019). A CCPS is characterised by its active engagement and adaptability to the environment, enabling it to perceive and interact independently with its context (Oliveira et al., 2019). The design of such systems requires the development of interfaces for environmental interaction, enabling a dynamic exchange of information, facilitating decision-making and enhancing human–machine interactions (Mizanoor Rahman, 2019). Thus, we propose a definition for CCPS that starts with the foundational concept of a CPS and enhances it with the capabilities of a cognitive system:

Definition 2. A CCPS is a CPS and a cognitive system. As such it as cognitive functions, with abilities enabling not only to interact with its environment, but also to understand and learn from it, to make autonomous decisions and adapt dynamically to the context.

As for CCPS, the Cognitive Digital Twin is the evolution of the DT where it is given cognitive functions. Our state of the art analysis highlighted key features like adaptability (Abburu et al., 2020b; Eirinakis et al., 2020; Yitmen et al., 2021), structured intelligence (Intizar Ali et al., 2021), semantic modelling (Li et al., 2022; Lu et al., 2020), autonomy (Zheng et al., 2022), and the symbiotic relationship with the physical system (Zheng et al., 2022). Globally, a CDT possesses properties of a cognitive system, completed with DT-specific ones. This forms a reference framework for a definition that not only captures the digital replication capacity of a cognitive system but also its dynamic evolution and autonomous interaction with its environment. We propose the following definition for CDT:

Definition 3. A CDT is a DT and a cognitive system. As a DT it emulates a physical system that can be or not itself cognitive. As a cognitive system it possesses cognitive functions, bringing it in particular the ability to semantically model, process and interpret information autonomously and actively learning from its interactions.

These definitions of CCPS and CDT, extended with ideas from cognitive systems, establish a foundation for cognitive interoperability. However, implementing this within a CPE is not trivial. As part of our systematic literature review, we highlight the concept of cognitive interoperability, historically associated with human dynamics and particularly underlined in the military sector (Klose et al., 2005) and emergency management (Kwon et al., 2011). This concept highlights the need for a shared mental framework that goes beyond the simple coordination of information and processes. Semiotic-cognitive interoperability explores the possibility of mutual understanding between humans and Berthier (2006) systems. In our view, this development illustrates the need for a deeper understanding of cognition for effective collaboration, based on shared meanings and not just information sharing. Until now, cognitive interoperability has been little explored and exploited in human–machine interactions (Gaffinet et al., 2023), and has not been widely implemented in the field.

6. Conclusion

The 5th industrial revolution starting now should be characterised in particular by the integration of CCPS and CDT, underscoring the fact that artificial systems are no longer just tools; they are collaborators. As enterprises evolve into CPE, the infusion of cognition capabilities into industrial systems becomes not just desirable, but imperative. In this paradigm, the role of cognitive functions becomes essential. In this context, cognitive interoperability becomes an important concern. But handling it will redefine human–machine collaboration, decision-making and knowledge sharing.

In this article, based on an extensive analysis of the literature, we have presented the foundations of cognition for its implementation in cognitive systems such as CCPS and CDT, and the concept of cognitive interoperability in CPE. We highlighted that cognition goes beyond simple data collection, also covering the transformation and use of knowledge for understanding, judgement and autonomous decision-making. We have examined the basic mental functions that make up cognition. These are those functions – perception, attention, memory, problem-solving, reasoning, decision-making and learning – that hybrid AI combining data-driven ML/DL and NLP approaches with knowledge representation and reasoning aspire to simulate. We have highlighted that despite its rapid progress and ability to identify patterns, sub-symbolic AI cannot yet match all cognitive abilities, especially when it comes to understanding semantic complexity and the structured representation of knowledge, which requires symbolic approaches. KRRs bring a level of accuracy and understanding to cognitive systems that goes beyond what is possible with ML alone. Finally, we have also pointed out that cognitive architectures, including complex architectures such as ACT-R, LIDA and SOAR, represent a significant advance when integrated with systems capable of managing and using knowledge. As systems dedicated to implement the human-way of thinking, cognitive architectures could provide a fundamental basis for the development of cognitive systems.

Despite the advances, challenges remain. Current research coupling CCPS with CDT are still limited in that they focus on the twinned CPS only, without considering enough interactions with its environment. Integrating multiple tools into a CDT could be a source of complexity, and distinguishing between static and dynamic features could pose synchronisation problems. The complex design and integration required by their semantic capabilities is a challenge, and real-time data management could put a strain on data processing and decision-making systems. In CCPS, one of the main challenges is to establish a framework of solid trust and mutual understanding between humans and these systems. In addition, their distributed and global design can lead to complexities in coordinating the various components, particularly in dynamic environments. Finally, cognitive interoperability, aimed at facilitating cooperation between heterogeneous systems at the level of cognitive exchanges, remains a major challenge to overcome for successful human–systems integration.

Progress has been made with Cognitive CPS and Cognitive DT, but there is much more to achieve to actually move from systems integrating AI components to systems, showing then cognitive behaviour. The key to success is integrating the principles of cognition with the practical applications and systems powered by AI. to enable real teamwork between humans and machines. As cognitive systems learn and adapt, ensuring they remain stable and predictable is essential. We need to take a comprehensive approach that covers everything from the software's design to its security and how people interact with it. Although the concept of machines working seamlessly with humans is well-recognised, making this a reality across different areas still requires some work. The social-cognitive interoperability approach highlights the importance of social factors in the implementation of cognition within systems. Therefore, we need to pay close attention to how cognitive and social elements work together in cyber–physical systems to foster cognitive interoperability, where there is great potential for cooperation that we have not yet fully exploited. And finally, to really see if we can emulate human cognition through Hybrid AI.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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