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# Industry 5.0 and its technologies: A Systematic Literature Review upon the human place into IoT- and CPS-based industrial systems\*

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## Abstract

Industry 4.0 has fueled research for almost a decade now. Beyond production efficiency, it has raised sustainability issues and societal challenges. However, these have mainly been driven by technological developments until now, putting aside the human and societal aspects. Faced with the emergence of paradigms such as Industry 5.0, it becomes clear that societal considerations are back on the technological and scientific stages. This paper is interested in the place that have been given to the human in last year's industrial research. More specifically, the focus have been set on the human aspect into Industry 4.0's main pillars: Cyber-Physical Systems and Internet of Things. Therefore, this work proposes a Systematic Literature Review on the subject. To apprehend the progress of research towards industrial systems as complex socio-technical ones, the retrieved literature has been analyzed through two frameworks: the enabling technologies for Industry 5.0 and the grounding concepts of systemics.

**Keywords:** Industry 4.0; Industry 5.0; Human-Systems Integration (HSI); Systematic Literature Review (SLR); Internet of Things (IoT); Cyber-Physical Systems (CPS)

## 1 Introduction

For the last decade, the initiative Industrie 4.0 [1], along with number of other national programs (Industrie du futur, High Value Manufacturing Catapult, Made in China 2020, etc.) have been taken as reference background for the development of industrial systems. By their impact, these initiatives are today commonly recognized as part of the 4<sup>th</sup> industrial revolution, also known as *Industry 4.0*, and globally responding to the same precepts [2]. Initially, Industry 4.0 was aimed to "*address and solve some of the challenges facing the world today such as resource and energy efficiency, urban production and demographic change*" [1]. From an industrial viewpoint, the most important challenge and maybe the easiest to apprehend, might be to head towards continuous resource productivity, and efficiency gains delivery across a globalized value network.

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To deal with demographic and social changes, Industry 4.0 have raised the attention on the need to rethink work organization. For instance, facing skilled workforce shortage, industries need to preserve their workers to extend their working lives, and to keep them productive longer. To this end, research on systems, such as smart assistance ones, have known a consequent growth. Notably, the recent appearance of the *Operator 4.0* concept, proposing a vision for human-automation symbiosis by enhancing "*human's physical, sensitive and cognitive capabilities by means of human cyber-physical system integration*" [3], can be evoked. These systems are designed to release workers from routine, wearing or dangerous tasks, to refocus them on creative and value-added activities. Besides, these developments equally aim to support flexible work organisation that, beyond being resilient, would enable workers to better combine their work and private lives, improving their work-life balance. Hence, it can be assessed that, in its initial conception, Industry 4.0 was destined to address and solve both technical and societal challenges, relying in particular on last decade's technological advances concerning Internet of Things (IoT) and Cyber-Physical Systems (CPS). This led to the rise of the debate around new *Work 4.0* paradigm in Germany [4], questioning the societal implications of Industry 4.0 into everyday work. Yet, it is today assumed that Industry 4.0 have stayed focused on CPS- or IoT-based general purpose technologies (technology-driven progress), somehow missing its societal scope.

To influence this dynamic, recent years have seen the appearance of a new paradigm, proposed as a societally-driven complement to Industry 4.0's hallmark features: the Industry 5.0. Broadly, Industry 5.0 can be seen as a corrective "patch" or "add-on" to the Industry 4.0, focusing on human-centric design, sustainability, and resilience. That is not to say that the technology is out of scope. Emphasis will be placed on technologies as a set of complex systems, combining technologies such as smart materials and embedded / bio-inspired sensors, enabling, securing, and strengthening human safety, well-being, and interactions into and with the industrial system, such as Augmented or Virtual Reality, collaborative robotics, etc. To this end, recent works of the [5, 6], involving European Union's technology leaders, proposed a set of relevant and enabling technologies for Industry 5.0. Besides, the reports from European commission [5, 6] equally point out the fact that a systemic approach for Industry 5.0 is necessary to support the above-mentioned technological enablers. Indeed, Industry 5.0 and its technologies are expected to face the social, ecological, economic, governmental and political challenges, left aside by Industry 4.0. Consequently, with regard to the industrial community research fields, the challenge is to strengthen human's trust and acceptance concerning those new technologies, developing inter- and trans- disciplinary in future works (to make engineering, life & social sciences, humanities, etc. converge), and ensuring their broad-scale implementation across value chains and ecosystems (scalability). Moreover, the concepts of sustainability, resiliency and human centric approach are complex by nature, with different meanings depending on the scientific discipline, the field of application, the time scale and the scale of industrial systems (current industrial system or new one), as well as the transformations/impacts they can have on new industrial system organizations. These led the authors to consider mainly one dimension and in particular: the question of the integration of the human component into the IoT- and CPS-based industrial systems. How is this integration envisioned, from a "system" viewpoint? What is the current state of development of so-called human-centred technologies? Thus, the paper proposes a Systematic Literature Review (SLR) focusing on the global integration of industrial systems' actors as a network of interconnected assets (artefacts & humans, objects & agents) within complex-adaptable systems [7]. Notably, what will be studied is the place given to the human component by the new concepts such as the IoT and CPS paradigms, to identify their potential for more human-centred development. This will help identifying the challenges to be explored to reach this vision of industry 5.0.

To this end, the rest of this article is organized as follow. 2<sup>nd</sup> section will provide a global overview of the IoT and CPS notions, as grounding concepts for Industry 4.0. The 3<sup>rd</sup> section will detail the methodology used to perform the SLR, based on Kitchenham’s recommendations [8]. Then, the 4<sup>th</sup> section presents the first numerical results of the methodology, along with a general analysis focused on quantitative aspects. This section also contains observations concerning 3 forms of sociability structuring 4 types of social systems, that can be made when taking a closer look to place of human aspects into IoT and CPS’s different developments. The 5<sup>th</sup> section is conducting qualitative analysis on the retrieved literature through 2 specific frameworks, questioning the "system" vision presents in the research results (systemic analysis), and the current development state of Industry 5.0’s technological enablers. 6<sup>th</sup> section brings discussion elements while the last one concludes the paper and proposes some research directions.

## 2 IoT and CPS: an overview

The importance of the CPS and IoT concepts have steadily been growing in the literature for the last decades. The notion of CPS is generally recognized as the main pillar of Industry 4.0. Due to its wide range of potential applications, this concept enjoys great popularity in the scientific literature although it is rather recent [9]. However, popularity and novelty make it a concept whose definition and limits are rather blurred. Besides, it is also often associated with the IoT, which appeared a little earlier. It seems that preferences in the use of the terms CPS and IoT are observed from one scientific community to another or from one geographical area to another. Thus, CPS will be preferred in mechatronics, and IoT will be preferred in computing societies [10, 11]. The term CPS will also be found more often on the American continent than on the European or Asian ones, where IoT will be preferred. However, these two concepts are in fact different and have to be differentiated.

Among the multitude of definitions that can be found in the literature, we will consider the IoT as: “*an open and comprehensive network of intelligent objects that have the capacity to auto-organize, share information, data, resources, reacting and acting in face of situations and changes in the environment*” [12]. In this definition, IoT is clearly seen as a link between physical objects within a system composed of multiple objects. Regarding CPS, it seems relevant to keep its initial definition provided by Lee: “*physical and engineered systems whose operations are monitored, coordinated, controlled and integrated by a computing and communication core. This intimate coupling between the cyber and physical will be manifested from the nanoworld to large-scale wide-area systems of systems. And at multiple time-scales*” [9]. The CPS concept therefore expresses a “coupling” between physical objects and their digital representation/twin. Considering these two definitions, we define a system as being composed of objects and their digital representations. This system is organized along 2 axes: the first one, representing the physical world; the second one representing the digital world (i.e. cyber). The IoT would then correspond to the horizontal connectivity/synchronization between objects and the notion of CPS would call the vertical connectivity/synchronization between objects and their digital representation [13] (Fig. 1). Hence, it can be assessed that CPS and IoT are constituting the 2 of today’s main enabling paradigms for Cyber-Physical Systems’ networking, and then for Industry 4.0, relying on the integration of objects, their virtual representation, and humans, as networks within complex-adaptable systems. Yet, these visions stay techno-centered, focused on machine-machine interactions.

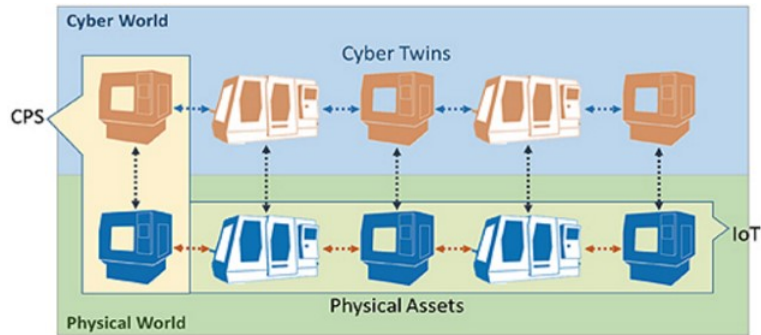


Figure 1: CPS & IoT [13]

### 3 Methodology for Systematic Literature Review

This section will expose the research protocol, accordingly with the SLR guidelines provided by Kitchenham [8]. The SLR methodology will allow to provide the most representative possible state of the art concerning the *human dimension* in *CPS* and *IoT*-related paradigms regarding different *industrial* context. Note that the general *manufacturing control* pole identified in the introduction is not included in the scope of this search, for previous works that will be presented hereafter already provided extensive review of the subject. To ensure the quality of this SLR, the paper selection method has been established using the 4 following recommendations from the Centre for Reviews and Dissemination (CRD)'s Database of Abstracts of Reviews of Effects (DARE)<sup>1</sup> [14].

- Relevant search-string and at least 4 databases shall be used to cover most of the related works;
- Inclusion and exclusion criteria must be explicit and appropriate, ensuring the relevance of the study;
- Accordingly to a set of pre-established criteria, the quality and validity of included studies shall be assessed;
- Included studies shall be synthesized, with emphasis on their relevant data/contents.

To conduct this study, more than 10 scientific digital libraries and databases have been identified. Yet, after a first search iteration, some turned out to be unsuitable for a search strings-based targeted search, or for results mass-extraction. Ultimately, the 8 following databases and digital libraries were used for this study: ACM<sup>2</sup>, BASE<sup>3</sup>, HAL<sup>4</sup>, IEEE Xplore<sup>5</sup>, Science Direct<sup>6</sup>, Scopus<sup>7</sup>, Taylor & Francis Online<sup>8</sup>, and Web of Science<sup>9</sup>.

<sup>1</sup>DARE: <https://www.crd.york.ac.uk/crdweb/ShowRecord.asp?ID=32004000332&ID=32004000332>

<sup>2</sup>ACM Digital Library: <https://dl.acm.org>

<sup>3</sup>Bielefeld Academic Search Engine: <https://www.base-search.net>

<sup>4</sup>Archive ouverte HAL: <https://hal.archives-ouvertes.fr>

<sup>5</sup>IEEE Xplore: <https://ieeexplore.ieee.org>

<sup>6</sup>Science Direct: <https://www.sciencedirect.com>

<sup>7</sup>Scopus: <https://www.scopus.com>

<sup>8</sup>Taylor & Francis Online: <https://www.tandfonline.com>

<sup>9</sup>Web of Science: <https://www.webofscience.com>

Search strings have been built based on 3 sets of keywords, each relating to one aspect of the search. The first one, searched by  $S_1$ , aims to review literature related to the CPS and IoT paradigms and their variants. To this end, the terms "*Cyber-Physical Systems*" and "*Internet of Things*" have been decomposed for more inclusion. The second search string,  $S_2$ , aims to limit the search to industrial context, using terms "*manufacturing*", "*production*" and "*industry*". The third one, is grounded on the keywords commonly used when considering the human aspect in literature, identified in previous studies [15, 16]: "*human*", "*anthropocentric*" and "*social*" ( $S_3$ ). The search strings are presented below, formatted using Boolean logic, as usual for digital library querying. These were eventually adapted, to better suit libraries' particular specifications.

$S_1$  : "(internet AND of AND thing\*) OR (cyber\* AND physical\* AND system\*)"

$S_2$  : "manufacturing OR production OR industr\*"

$S_3$  : "human\* OR anthro\* OR socio\* OR social\*"

The query  $R$  supporting this SLR will then be the association of  $S_1$ ,  $S_2$ , and  $S_3$ . Consequently, the literature scan will consist in querying each of the bibliographic database previously listed with the following search.

$R = S_1 \text{ AND } S_2 \text{ AND } S_3$ : "((internet AND of AND thing\*) OR (cyber\* AND physical\* AND system\*)) AND (manufacturing OR production OR industr\*) AND (human\* OR anthro\* OR socio\* OR social\*)"

The papers selection and exclusion process was carried out in 3 stages. First selection step occurred directly during databases querying, with the following criteria:

- To avoid papers with no close bound to the search, the string  $R$  was not used for a full-text search, but focused on papers topic i.e.: title, abstracts and keywords;
- English-written papers: for the sake of homogeneity, and to guarantee the international scope of the study;
- Timespan: 1990 - 2021, for IoT and CPS paradigms are no prior to 1999.

Second step was performed upon the aggregation of the results from initial search  $R$  into each database:

- Removal of duplicates;
- Removal of papers not consistent with initial research criteria;
- Removal of non-JCR publications. Only publications indexed to the Journal Citation Report(JCR), a reference framework attesting the quality of a journal, were targeted.

Third and last step was performed manually by the authors upon the remaining papers:

- Title, abstract & keywords analysis: removal of papers that are not closely related to the searched topic, and enables a first general analysis of the literature;
- Full-text reading: removal of papers for which an ambiguity persists, enabling an in-depth analysis of the literature.

In absolute terms, these two consecutive filtering shall be performed before any further analysis. However, full-text readings can only be performed on available documents, whose may turn out to be considerably fewer than those identified after the title-abs-key analysis. Moreover, considering the time required for the careful reading and understanding of a journal paper, this last step has to be conducted on an consequently narrowed amount of papers. For these reason, the general analysis of the literature was performed right after the title, abstract & keywords filtering, upon the metadata extracted from retained papers. Then, full-text reading and in-depth analysis were conducted upon the retrieved available papers.

## 4 General analysis

Table 1 presents the results of the query  $R$  for each one of the databases previously exposed. Figure 2 synthesizes the followed papers-retrieving methodology and its step by step results. Thanks to this selection process, the initial sample of more than 3 500 results was significantly reduced down to 149 exploitable bibliographic entries.

**Table 1:** Number of papers retrieved from each database

Queried databases	Results for $R$
ACM	91
BASE	42
HAL	49
IEEE Xplore	361
Science Direct	150
Scopus	1671
Taylor & Francis	7
Web of Science	1186
Total	3557

First noticeable thing is that, despite the fact that the search is covering a period from 1999 to 2021, only papers from 2011 to 2021 were retrieved. In addition, Figure 3 shows that a consequent and steady raise of interest could only be noted from 2016. It can therefore be assessed that the question of humans' place in CPS and IoT literature regarding industrial issues is rather recent, even though those concepts are independently much older and studied.

Second, each contribution has been associated to the nationality of its authors' home universities. It then can be observed that around 40% of the retrieved papers are international collaborations. Besides, figure 4 reveals that China is by far today's main contributor, having produced or participated to more than 30% of current literature. Unsurprisingly, since this study is questioning the future of industrial systems, the others main international contributors being among the most industrialized ones (Spain, USA, UK, Germany, India, Italy, Canada, France, etc.).

Third observation concerns the journals represented by this sample. The 149 retrieved papers have been published into 84 different JCR journals, which is a relatively high number. Hence, 11 journals presents 3 times of more are representing 42% of the sample (Fig. 5). Most of these journals being related to industrial engineering, computer sciences, or technological research, those

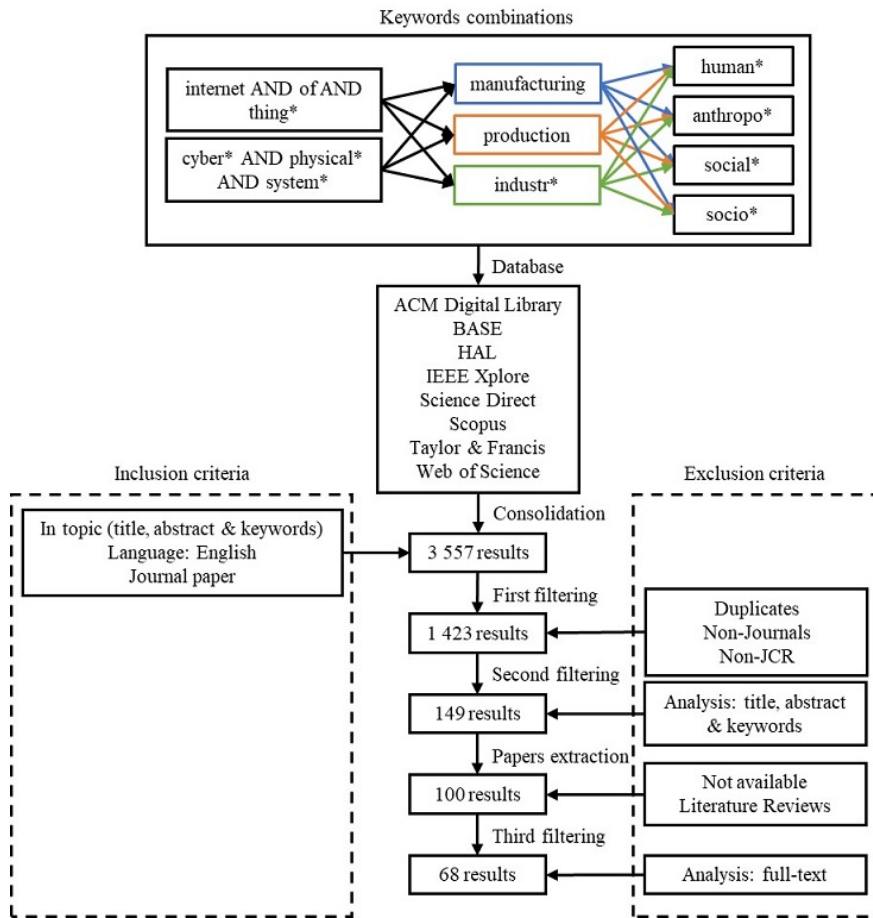
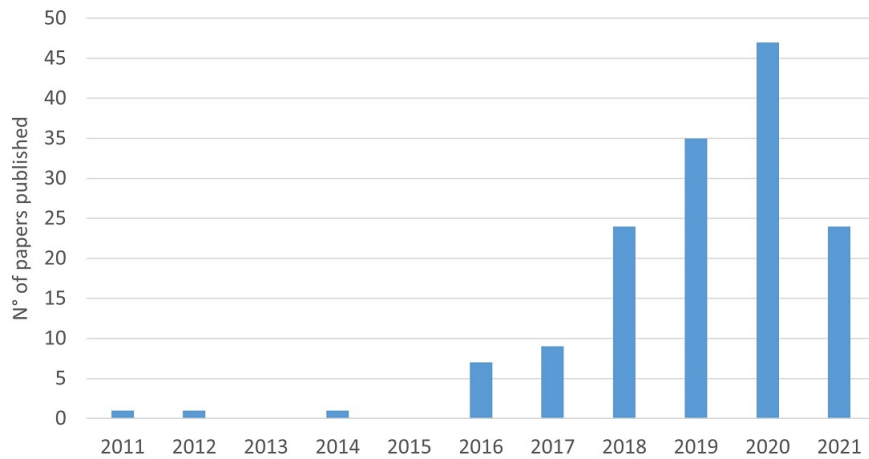


Figure 2: Papers retrieving methodology

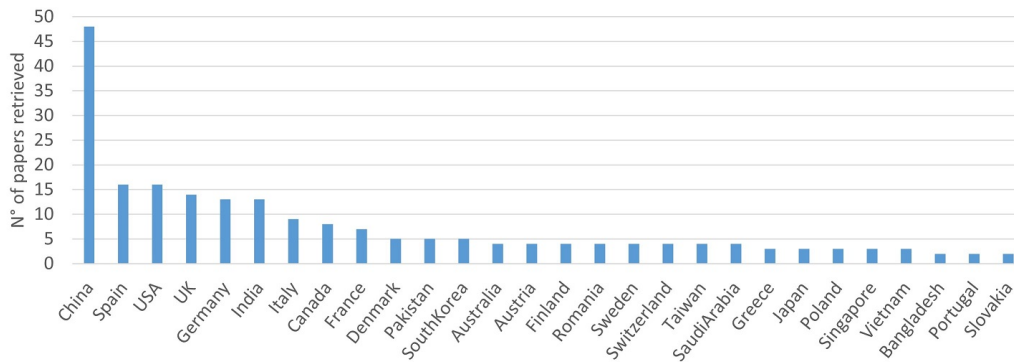
approaches can be stated as largely dominating the retrieved literature. For instance, the largely represented *IEEE Access* is relating to general engineering and computer & material sciences. Among the most represented ones, the *IEEE Transactions on Industrial Informatics*, *Computers & Industrial Engineering*, *Journal of Manufacturing Systems*, *IEEE Internet of Things Journal*, *Sensors*, *Future Generation Computer Systems*, *International Journal of Production Research*, or *Computers in Industry* journals can equally be cited. Nonetheless, several journals seems to be focused on more safe (*Process Safety and Environmental Protection*), sustainable (*Sustainable Computing-Informatics & Systems*), and human-centric (*Applied Ergonomics*, *Social Behavior and Personality*, *International Journal of Human-Computer Studies*) developments.

The fourth and last element highlighted by this sample's analysis is the co-authorship among papers. The analysis of the sample's metadata shows that only 48 out of the 567 retrieved authors and co-authors proved to have participated to 2 or more papers. In addition, even if the interest for the subject is rising since 2016, the authors retrieved by the co-authorship mapping only published between 2018 and 2020. This globally denotes a rather new interest for the subject, led by small independent, yet international communities.



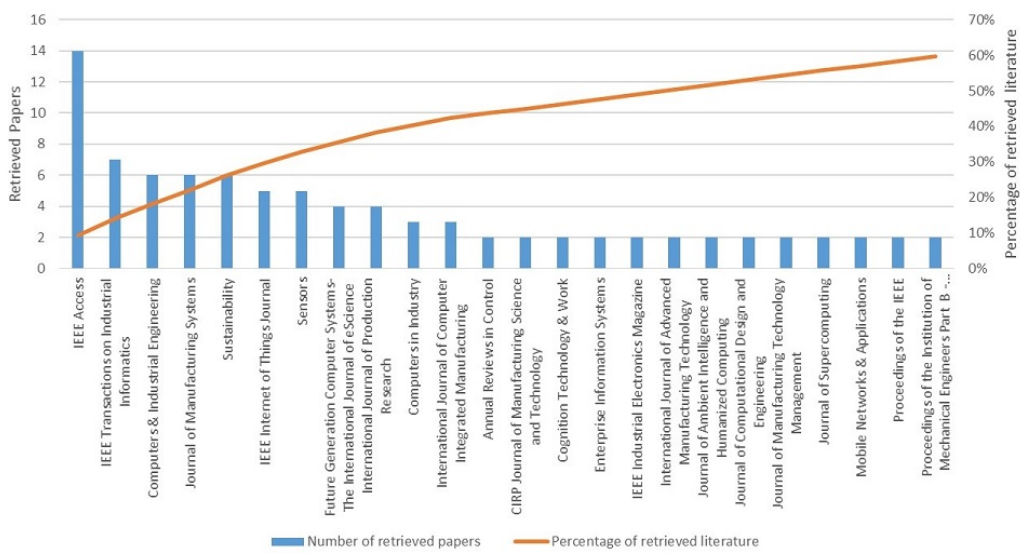


**Figure 3:** Number of papers published per year



**Figure 4:** Number of papers published per country

It can be summarized that research concerning the human dimension in industrial systems regarding the CPS and IoT paradigms has only recently become an important subject. Advances in this field are today notably supported by strongly industrialized countries, with great international cooperation. Yet, the subject is still emerging and the research community fragmented. Based on a first reading, more than 10 IoT and CPS variants can already be identified. Those variants can be considered as mostly differing by their application domain, enabling technologies, and system structuring & organization. Table 2 already summarizes the main characteristics of the most notable ones. Two aspects in these variants seem particularly relevant to study in this work. First, to characterize and analyze these systems' approach regarding the human factor, a systemic framework will be established and used. Then, the enabling technologies supporting these systems will equally be analyzed through a second framework. Next sections details these frameworks more precisely and will presents the result of the literature analysis through them.



**Figure 5:** Journals representation in retrieved sample

**Table 2:** IoT and CPS variants in retrieved sample

<b>Term</b>	<b>Definition</b>	<b>References</b>
ACPS	Anthropocentric Cyber Physical System: Reference model for factory automation integrating both physical, cyber, and human components.	[17]
CPHS / HCPS	Cyber Physical Human System/Human Cyber Physical System: Framework for smart manufacturing, integrating human, physical elements and cyber-technologies. Human cognition and learning are enacted by IoT devices to improve human-system interaction.	[18, 19, 20, 21, 22, 23]
CPIS	Cyber Physical Integrated Society: A society where cyberspace and real world are connected through networked IoT devices.	[24]
CPPS	Cyber Physical Production System: A system based on the progress of computer science, Information and Communication Technology (ICT), sensor and network technologies, including information systems and hardware resources, and supporting human-machine communication.	[25, 26, 27, 21, 28, 29]
CPSS / SCPS	Cyber Physical Social System/Socio Cyber Physical System: Integration of both social data, acquired from social networking platforms, and human data, acquired from sensors or human-system interfaces, into CPS.	[30, 31, 32, 2, 33, 23, 26, 34, 35, 36]
HitL	Human in the Loop Cyber Physical System: In a smart factory context, a CPS where IoT development enables human performance integration, by measuring human cognitive activity through body and brain sensors.	[19, 23]
ICPHS	Industrial Cyber Physical Human System: Industrial systems in interaction with humans and complying with societal norms and expectations, including ethical aspects.	[18]
IoP	Internet of People / Persons: Persons location data acquired using Wi-Fi system logs, or any portable connected device.	[37, 24]
SHITL	Social Human-in-the-Loop Cyber Physical Production System: A human-centered manufacturing system framework where many agents collaborate and are socially connected at both physical and cyber levels.	[38]
SIoT	Social Internet of Things : A network of communicating objects/assets able to autonomously build their own structuring social relationships without human intervention. Those social relationships are coming from human social network services and media.	[39, 40, 41, 42, 30, 43, 44, 45, 46, 47, 48]
SIoIA / SIoIT	Social Internet of Industrial Assets/Social Internet of Industrial Things: Application of SIoT to industrial assets to reduce human inputs and then limit human-related disruption in the system.	[40, 47]
SM	Social Manufacturing: A cyber-physical-social connected and service-oriented manufacturing paradigm, where an IoT-based production structure delivers service-oriented transformations to a social network of prosumers.	[31, 32, 23]

## 5 Systemic and Technological analysis

This section details the analysis of the retrieved sample through 2 frameworks: one systemic, the other technological. Table 3 details more precisely these frameworks. Each of these analyses is supported by a graph presenting the research interest shown in the analyzed literature sample for each of the frameworks axes. It goes without saying that a publication can be related to several categories. The first analysis conducted onto the retrieved sample was intended to confront it to the 4 basic grounding concepts of systemics [49], namely *Interaction/Interrelations*, *Wholeness*, *System/Organization*, and *Complexity*. The second analysis conducted onto the retrieved sample was intended to confront it to the technological enabling framework for Industry 5.0. According to the report from the [5], this framework is organised around 6 interrelated axes, namely *Human-centric solutions & human-machine-interaction*, *Bio-inspired technologies & smart materials*, *Real time based digital twins & simulation*, *Cyber safe data transmission, storage & analysis technologies*, *Artificial Intelligence* and *Technologies for energy efficiency & trustworthy autonomy*.

### 5.1 Systemic Framework analysis

#### 5.1.1 Interaction/Interrelations

If, from a static viewpoint, a system can be defined as a set of interacting elements, then it can be deduced that the nature of a system emerges from both the nature of its component and the nature of their interaction. Concerning the *Interaction/Interrelations* concept, the notion of interaction focuses on the relationships between the elementary components of a complex system taken two by two. It can relate to influences or exchanges of matter, energy or information among system's components, the nature of these interactions being even more important to know than the one of the components themselves. More specifically, the study of the IoT and CPS variants presented by table 2 showed that human aspect integration into CPS and IoT systems was realized through different interaction or sociability models (Table 4), ultimately aiming to ease the integration of human or any social systems into automated production systems [50, 7]. The first model is proposing interactive interfaces or embedded sensing systems to enable human-system interaction. The second one uses the structure of existing social network services, that are offering numerous features and data to

**Table 3:** Systemic and Technological frameworks

Systemic Framework	Interaction/Interrelations
	Wholeness
	System/Organization
	Complexity
Technological Framework	Human-centric solutions & human-machine-interaction
	Bio-inspired technologies & smart materials
	Real time based digital twins & simulation
	Cyber safe data transmission, storage & analysis technologies
	Artificial Intelligence
	Technologies for energy efficiency & trustworthy autonomy

establish a socialization-based internet. The last model relates to the design of an industrial system as a society, linking smart connected objects through a typology of social relationships. Thus, the 3 following types of sociability can be identified:

- Social interactions based on peer-to-peer communication interfaces, where almost any interaction among two agents can be considered social. This approach is mostly found in Multi-Agent Systems (MAS) research field;
- Human-inspired social relationship based sociability model, where human-inspired social relationships are transposed into technical or socio-technical systems to structure them. For instance, those social relationships can be based on anthropological sociology works such as Fiske's ones [51].
- Social-Network Services (SNS) based approach as a media for social interaction, where "social interaction" refers to the use of Social Networking platforms' architectures to structure human-human, machine-human, or machine-machine data exchanges. Social Networking platforms and services being commonly referring to services such as Facebook or Twitter, due to the vast amount of data they could provide, or more occasionally to specifically developed platforms;

The use of these 3 sociability types to study the literature sample shows a certain unbalance (table 4). The majority of the studied literature considers social interactions as simple peer-to-peer communication interfaces either between systems and systems, or between human and system (around 57%). Besides, approximately 26% of the papers, mainly supporting SIoT developments, are considering social interactions as SNS-based approaches. These two approaches are in fact clearly expressing a neat distinction between human and technical systems. Yet, the systemic vision of socio-technical systems implies to consider technical and human systems as a whole, and only in few works are social interaction considered as an extension of human sociological models to technical systems.

**Table 4:** Sociability type distribution in the retrieved sample

Sociability type	References
Social interactions based on peer-to-peer communication interfaces	[37, 52, 2, 21, 29, 31, 53, 54, 55, 56, 57, 28, 58, 59, 60, 61, 62, 26, 18, 63, 64, 25, 46, 65, 27, 66, 17, 67, 68, 20, 69, 47, 48, 70, 71, 22, 72, 38, 73, 74]
Social-Network Services based approach as a media for social interaction	[36, 41, 42, 30, 45, 43, 34, 40, 75, 32, 76, 77, 78, 79, 80, 39, 35, 33]
Human-inspired social relationship based sociability model	[19, 81, 23]

### 5.1.2 Wholeness

Considering the *wholeness* basic concept, it is defined as expressing "*both the interdependence of elements of the system and the coherence of the whole*" [49]. This definition can be associated with the words of Ludwig von Bertalanffy when defining its General System Theory (GST): "*You*

cannot sum up the behavior of the whole from the isolated parts, and you have to take into account the relations between the various subordinated systems and the systems which are super-ordinated to them in order to understand the behavior of the parts"[82]. This idea theorizes the emergence phenomenon occurring within complex systems: at the global level are appearing properties that can not be deduced from elementary properties. Wholeness defends the idea that a system is more than the sum of its parts, but also of its interactions with other systems of whatever nature. More particularly, in our context, this concept implies to consider technical and human systems as a whole. To this end, 4 types socio-technical systems, based on these 3 types of sociability can be identified (see figure 6). When considering fully technical system, the P2P Communication Interface-based sociability model is supporting *technical systems of communicating objects*. When considering both human and machines, this same sociability model simply supports *technical systems interacting with humans*. A system of communicating objects structured by SNS-based sociology is called a *social network of communicating objects*. Finally, a system of human and cyber-physical agents structured by human-like social relationship (anthropo-social model) is called a *social network of socio-technical agents*. Table 5 and figure 7 are showing the distribution of our sample regarding this framework. On these elements, it emerges quite clearly that systems are today still not really considered as intrinsically socio-technical ones. Instead of that, it can be stated that the quasi-totality of papers are considering human/social and technical systems as two separate entity. In these papers, contributions are mostly relatives to communication interfaces or mechanics/relationships transposition between one kind of system and another.

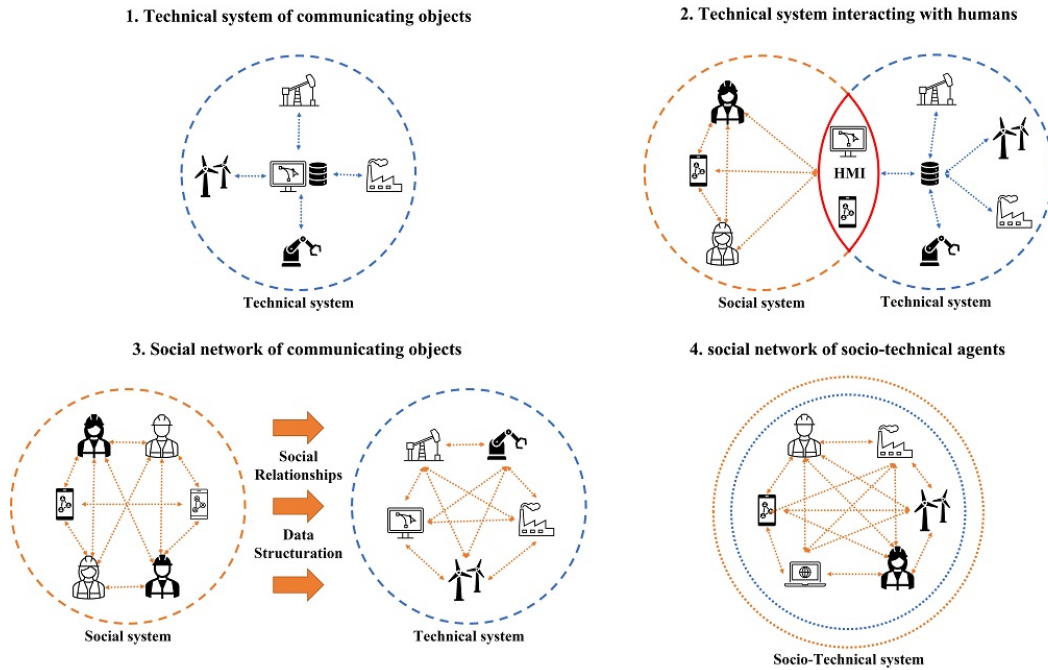
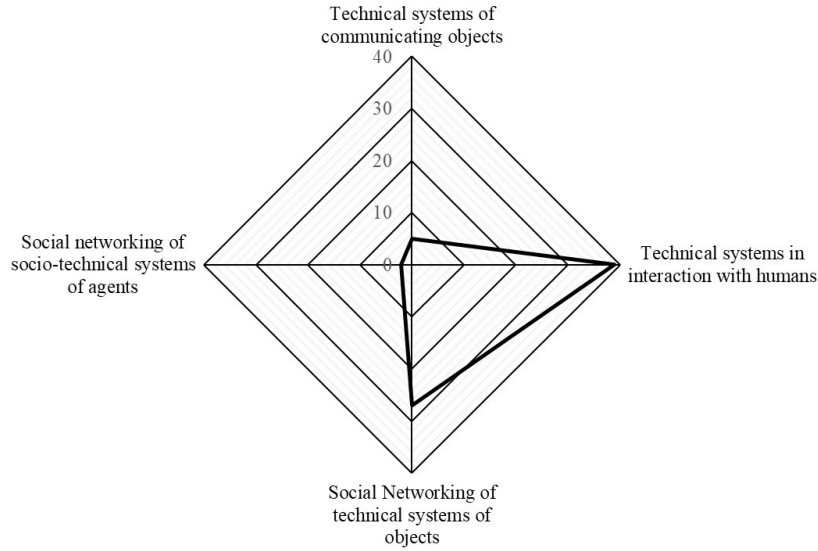


Figure 6: The 4 types of social systems

**Table 5:** Socio-technical systems distribution in the retrieved sample

System type	References
Technical systems of communicating objects	[62, 24, 67, 43, 52]
Technical systems interacting with humans	[37, 62, 66, 69, 65, 20, 38, 68, 83, 76, 26, 35, 55, 21, 64, 73, 28, 59, 72, 58, 71, 17, 29, 22, 84, 25, 31, 79, 53, 60, 32, 80, 54, 56, 85, 48, 63, 57, 61, 86]
Social networks of communicating objects	[81, 39, 38, 78, 40, 35, 42, 30, 24, 75, 18, 87, 44, 88, 45, 31, 46, 70, 74, 77, 32, 80, 2, 33, 47, 48, 23]
Social networks of socio-technical agents	[36, 19]



**Figure 7:** Number of publications regarding the system's nature

### 5.1.3 System/organization

The *system/organization* basic concept can be summarized as focusing on the organization of the constituents of a system as a coherent whole. It can be considered as the very grounding of systemic approach. According to the Systems Engineering Body of Knowledge (SEBoK)<sup>10</sup>, the most commonly used definition of a system found science is given by the GST: "*A System is a set of elements in interaction*" [82]. To this broad definition, the works from [89] and [90] added two aspects: first, the system's element are in *dynamic* interaction and second, they are *organized* according to a goal. In the context of systemic approach, this concept will refer to what makes this set of dynamically interacting and goal-pursuing elements a *coherent whole* [49]. This coherence is achieved through

<sup>10</sup>SEBoK: [https://www.sebokwiki.org/wiki/Guide\\_to\\_the\\_Systems\\_Engineering\\_Body\\_of\\_Knowledge\\_\(SEBoK\)](https://www.sebokwiki.org/wiki/Guide_to_the_Systems_Engineering_Body_of_Knowledge_(SEBoK))

the organization of the elements. Here, organization refers to both a structural and a functional aspect i.e.: how is built/arranged the whole, and what this arrangement allows it to do. This arrangement can be done in 2 ways: organization in modules/subsystems, that integrates pre-existing systems as broader systems, and organization in hierarchical levels, new properties are produced and added at each level. In the industrial context, this relates to the notion of control modes and architectures that have been detailed in the 1<sup>st</sup> chapter. Notably, *system/organization* is expressed by the intrinsic centralized or decentralized nature of the considered (sub)systems (i.e.: hierarchy, heterarchy, isoarchy). This nature can be found at different levels, from the global system’s control architecture [17], to the local functioning of a specific subsystem such as resource sharing module [77]. Even if this organizational aspect is not part of the initial search, Table 6 shows that it is observable into many of the systems exposed in the retrieved papers. Equally, a clear tendency to develop decentralized systems can be noted. This can be simply explained by the very nature of SIoT-based systems, upon which many developments are today conducted but also by the new vision of good work for digital age with some new expectations (income and social security, considering co-determination, participation and corporate culture as a whole, variety as the new normal: a life-phase approach rather than rigid work models...) [7], leading to the emerging new socio-technical systems combining Lean thinking and production practices with new technologies and human factors [91, 92].

**Table 6:** Organization type distribution in the retrieved sample

Organization type	References
Hierarchical	[56, 45, 43, 62, 26, 18, 24, 27, 80, 38, 33]
Heterarchical	[52, 2, 21, 29, 31, 42, 30, 62, 75, 64, 17, 32, 48, 77, 78, 79, 38]
Isoarchical	[65, 20]

#### 5.1.4 Complexity

The last basic concept of the systemic approach, *complexity*, refers to the difficulties for analytical and rationalist methods to fully apprehend systems. In a complex system, many components of various nature are interacting with each other, generating emergent and non-linear behaviors, and conferring the system spontaneous ordering characteristics and adaptation abilities. A system’s high degree of organization, uncertain or unstable environment, and more globally the impossibility to identify, quantify and master all the elements and relationships at stake are likely to explain these phenomena. Undoubtedly, current and future industrial systems are complex. Computerization and the addition of the cyber world to the physical one pushed back the factories’ borders, multiplying the number of agents, data, exchanges, etc. tangible or not and overwhelming traditional system synthesis methods [93]. Complexity is the concept that gives full meaning to the development of systemic approaches for, without it, classical analytical methods would have been enough to fully apprehend and master all kind of systems. This complexity has not been studied in detail here. However, the models studied show the dominance of non-analytical approaches, such as MAS or Knowledge Management ones, to deal with it.



## 5.2 Technological Framework analysis

### 5.2.1 Human-centric solutions & human-machine-interaction

The *Human-centric solutions & human-machine-interaction* pole is presented as aiming to technologically support and enhance human physical and cognitive abilities. To develop the supportive dimension, a first focus has been set on enhancing the system/machines's grasp of different physical or cognitive human factors (Table 7). To do so, recent research have focused on the development of technologies for human speech, gesture, action and intention recognition & prediction [58, 53, 63, 25, 84, 73] or aiming to track humans' mental or physical strain & stress [36, 41, 63, 85, 68, 76, 72]. On the other hand, to enable the human to get a better grasp of their environment and to better interact with the system/machines, technologies mixing virtual and real worlds have taken a more and more important place. This is the case of Virtual Reality (VR) simulating a virtual and immersive environment with which the user can interact [61], Augmented Reality (AR) superposing in real time virtual elements and information to the real world [86], and Cross or Mixed Reality (MR) going even beyond VR and AR merging physical and cyber worlds to create an interactive cyber-physical hybrid reality, in which humans can evolve [59]. As for the enhancing dimension, focus has been set on both physical and cognitive capabilities. In the retrieved literature, cognitive enhancement is mostly achieved by developing flexible interfaces or technological devices providing relevant data/information to the user, and developing its sensing, learning and decision-making abilities [21, 59, 19, 67, 69]. When saying "physical enhancement", one would immediately think of exoskeletons-type devices and working gears. Yet, safety and physical condition tracking devices [85, 22] are equally part of human physical empowerment as part of industrial systems, along with remotely piloted devices [61]. This last device category calls for the 6<sup>th</sup> aspect of the pole identified by the European Commission: Human-Robot collaboration, or *Cobotics*, that is receiving considerable attention in the literature [29, 26, 19, 25, 65, 27, 66, 79, 80, 72].

**Table 7:** Human-centric solutions & human-machine-interaction

Focus	References
Multi-lingual speech and gesture recognition and human intention prediction	[56, 58, 61, 63, 25, 84, 71, 73]
Tracking technologies for mental and physical strain and stress of employees	[36, 41, 63, 66, 85, 68, 76, 71, 72]
Augmented, virtual or mixed reality technologies, for training and inclusiveness	[53, 59, 61, 86, 85]
Enhancing physical human capabilities (Exoskeletons, bio-inspired working gears, and safety equipment)	[21, 29, 61, 85, 69, 22]
Enhancing cognitive human capabilities	[21, 28, 59, 18, 19, 25, 67, 69, 48, 38]
Cobotics	[29, 26, 19, 25, 65, 27, 66, 79, 80, 72]

### 5.2.2 Bio-inspired technologies & smart materials

The *Bio-inspired technologies & smart materials* pole is focusing on the potential applications of bio-inspired technologies and processes into the industrial landscape. According to the European Commission report, those could be integrated with either green properties (Self-healing/repairing, recyclability, re-usability of wastes into raw materials, etc.), or with properties inspired by or adapted to biological systems (living, lightweight and intrinsically traceable materials, embedded biosensors, ergonomic systems). As highlighted in Table 8,3 of these tracks particularly stand out in our sample. The most represented one would concern the development and implementation of embedded- and bio- sensors technologies as key technological components for Human System Integration, by tracking and enhancing human physical & cognitive abilities [31, 63, 76, 71, 80]. Then comes the focus on ergonomics. While sensing technologies can be presented as HSI enablers, ergonomics is their application framework, for it consists in a multidisciplinary research field aiming for human's comfort, safety and productivity increase within its work environment [68]. Better ergonomics being achievable, for instance, through better operator positioning [72], thanks to technologies such as virtual, augmented or cross reality [59], or by better workshop organisation and visual clues [64]. The last property addressed into the studied sample is the self-healing and repairing ability of system's components. This last property is implicitly concerning smart products and materials, such as self-healing polymers [94]. Yet, when considering physical or cyber systems, developing self healing and repairing starts with the development of health, errors and failures detection. To this end, works have been conducted aiming to track industrial assets health as part of a social network of things [42], or to detect and treat time series outliers to ensure data quality [34]. We can assume that the other above-mentioned properties (living, lightweight, intrinsically traceable, recyclable, or re-usable as raw materials) are missing from our research sample for these notions were not aimed at by the search string *R*.

**Table 8:** Bio-inspired technologies & smart materials

Focus	References
Self-healing or self-repairing	[42, 34, 26]
Lightweight	/
Recyclable	/
Raw material generation from waste	/
Integration of living materials	/
Embedded sensor technologies and biosensors	[31, 56, 63, 67, 32, 76, 71, 79, 80, 73]
Adaptive / responsive ergonomics and surface properties	[59, 64, 68, 72]
Materials with intrinsic traceability	/

### 5.2.3 Real time based digital twins & simulation

The *Real time based digital twins & simulation* pole (c.f. Table 9) is focusing on products, processes, systems and systems' components modeling and simulation for optimization, testing or security purposes. One of the greatest challenges in today's industrial systems still lies in their control. Perfectly controlling any system implies in the first place to have a perfect knowledge of it. In the context of complex large-scale industrial systems, only relevant multi-scale models can provide this knowledge. For this reason, many works are today aiming to develop reference meta-models, frameworks, and architectures for industrial systems control [36, 53, 46, 83], for analyze and learning purposes [36, 53], or even for trust evaluation [46]. What modeling equally makes possible is the simulation of products and processes that can be used for their optimization [56], or to measure impact of different variables on the system and its environment (physical, social, environmental, etc.) [52, 2, 57, 60, 95]. But maybe the most trendy technology of this pole in current research concerns the development of Digital Twins. Digital Twin consists in a virtual replica of a physical system, product, resource or even human that can be used for design [83], monitoring [54, 58, 70] or optimization [56]. More specifically, in the studied sample, monitoring applications are the ones that are mostly retrieved and are mainly considering HMI and HSI finalities. Yet, systems monitoring aspects equally naturally covers real-time systems modeling, simulation and maintenance issues, for which Digital Twins can be of great use. By integrating physical assets in the cyber space, Digital Twins can be considered as one of the main enabling technologies for CPS development in the context of future industrial systems [17, 80, 23].

**Table 9:** Real time based digital twins & simulation

Focus	References
Digital twins of products and processes	[54, 56, 58, 83, 70]
Virtual simulating and testing of products and processes	[21, 56, 45, 75]
Multi-scale dynamic modelling and simulation	[36, 53, 30, 88, 43, 75, 46, 27, 17, 83, 47, 95, 78, 80, 38, 23, 74]
Simulation and measurement of environmental and social impact	[52, 2, 57, 60, 95]
Cyber-physical systems and digital twins of entire systems	[58, 17, 78, 80, 23, 74]
Planned maintenance	[42, 40, 20]

### 5.2.4 Cyber safe data transmission, storage & analysis technologies

The harmonious integration of these new technologies into current already complex industrial systems is one of their major challenges today. A key to achieve integration lies in these technologies' capacity for interoperability with each other, and with pre-existing systems, to form a coherent system of systems. This need for interoperability can be found at every level, whether it concerns structural & organizational aspects (such as enterprise systems' interoperability [43]), or technical and applied

ones (such as cyber & physical systems overlapping thanks to visualization interfaces for Cross, Mixed or Enhanced reality [59, 35]).

To enable and support this interoperability, the *Cyber safe data transmission, storage & analysis technologies* pole (c.f. Table 10) is focusing on the management and securing of the large amount of data that are and will be generated by all the previously enunciated technologies. From their acquisition thanks to sensors technologies or their creation by model-based simulation to their exploitation into real-time and multi-scale models, Digital Twins, etc. data management implies many aspects that already constitute the spine of today's industrial computer systems. Networked, wireless or not, sensors nowadays enable consequent data acquisition and transmission into industrial systems. Notably, last decades' consequent raise of embedded internet-connected devices (smartphones, tablets, laptops, etc.) have seen the emergence of the concept of "Social sensing", where human-related data are directly collected through these nomadic connected devices [31, 76]. After acquisition, data need to be efficiently and safely transmitted, stored, processed and analyzed. The great novelty regarding those tasks lies in fact in the size and complexity of data sets, for which traditional data processing methods and application software prove insufficient. The need to fill this gap fostered the development and use of Artificial Intelligence (AI) technologies and techniques. Notably, Big data management aims to make data usable for further analytic or learning application [71]. This learning aspect has taken a particularly important place in today's research. Current computing capacities coupled to the vast amount of available data have revived the development of neural networks and of machine, deep, and reinforced learning technologies. These can find very concrete industrial applications, for instance through modeling [36, 53], decision making and support [42, 24], human action recognition [61, 84, 73], human-machine interaction [58, 71, 33], or even human behaviors transposition to networked assets [75]. Hence, it can be assessed that data and computer systems' importance is vital for industrial systems. In the context of a globalized and hyper competitive economy, the development of scalable and multi level cyber security takes on its full meaning. Various approaches can be found in literature, from physical identification systems for access and authorization providing [55, 62] to data and assets trustworthiness evaluation [46]. In this search for secure, efficient and interoperable data management, a last aspect was identified: data traceability. If not particularly treated as the main topic of retrieved papers, identification and traceability issues can be retrieve in literature as an underpinning requirement in data management [55, 40, 24].

### 5.2.5 Artificial Intelligence

The *Artificial Intelligence* pole (Table 11) is mainly focusing on advanced data analysis and learning technologies. Advanced data analysis aims to handle and analyze complex, interrelated and dynamic data sets from different origin and scales. Thanks to AI, either causality- or correlation-based relation and network effects within various systems (artefactual or human), can be analyzed and transformed into exploitable data sets for modeling or learning technologies. Yet, while "traditional" correlation-based AI can identify correlation between actions and disturbances in psychomotor work [57] to build predictive experience-based models [87], causality-based AI (or causal AI) goes further. Based on the precise identification of cause and effect relationships between variables, causal AI is focused on the understanding of intrinsic systems' mechanisms. Hence, while correlation-based AI will be able to provide more or less accurate predictions (according to its training model and available data set), causal AI aims to provide reliable decision-making models and tools [96, 97]. Hence, causality based-models have to handle even more complex, yet fundamental, mechanisms. These concepts are underpinning the *Swarm/Distribute* intelligence technologies, aiming to make "clever" behaviors appear from stigmergy among a population of agents structured by simple rules. From a practical standpoint, beyond their analysis abilities, AI technologies are today the subject of

**Table 10:** Cyber safe data transmission, storage & analysis technologies

Focus	References
Networked sensors	[31, 42, 30, 88, 76, 79, 73]
Data and system interoperability	[30, 59, 43, 39, 35]
Scalable, multi-level cyber security	[29, 55, 62, 66, 81, 79, 72]
Cyber-security/safe cloud IT-infrastructure	[46]
Big data management	[58, 71, 23]
Traceability	[55, 56, 40, 24, 85, 48, 79, 23]
Data processing for learning processes	[36, 53, 56, 42, 58, 61, 24, 75, 84, 71, 33, 73]
Edge computing	[34]

great expectations regarding their ability to learn. AI research field covers many learning technologies, the most common ones being usually classified into *Supervised*, *Unsupervised*, and *Reinforcement* learning broad categories [98]. Aside from these 3 categories, Deep learning has today become extremely important in research landscape as a 4<sup>th</sup> full-fledged approach [75, 25, 33, 73]. Deep learning can be seen as based on Neural Network architectures, able to process the huge amount of data previously mentioned, to reach and even surpass performances of human experts in many domains. Industrial applications of Deep learning would today consists in human-activity recognition for Human-Robot Interaction (see human-centric solutions & human-machine-interaction pole), skills and requirements matching of tasks and operators [25, 20, 70, 33], or to enable systems to autonomously handle unexpected issues (which is one of the main issues regarding automated systems) [87, 20, 70]. Another interest of Deep-learning lies in recent developments of the Artificial Neural Network technologies aiming to reproduce biological (human- or animal-like) neural networks (e.g.: convolutional neural network [58]). These would later contribute for instance to enable/ease individual & human-centric AI [33, 73], or brain-machine interfaces conception.

### 5.2.6 Technologies for energy efficiency & trustworthy autonomy

The *Technologies for energy efficiency & trustworthy autonomy* pole is focusing on neutralizing the environmental impact related to all these new technologies' energy consumption (Table 12). Tomorrows' industrial systems will require huge amount of energy, in a world where the need for a sustainable development has become self evident. According to European Commission [5], focus should be set on renewable energy sources, Hydrogen and Power-to-X technologies, Smart dust and energy autonomous sensors development & integration, and low energy data transmission & data analysis. In the retrieved sample these elements are standing out, even if out of search range at first glance, through Energy Mobility Networks [52], Green/Energy-efficiency IoT [77] and AI [75] or Prosumer Community development [39].

**Table 11:** Artificial Intelligence

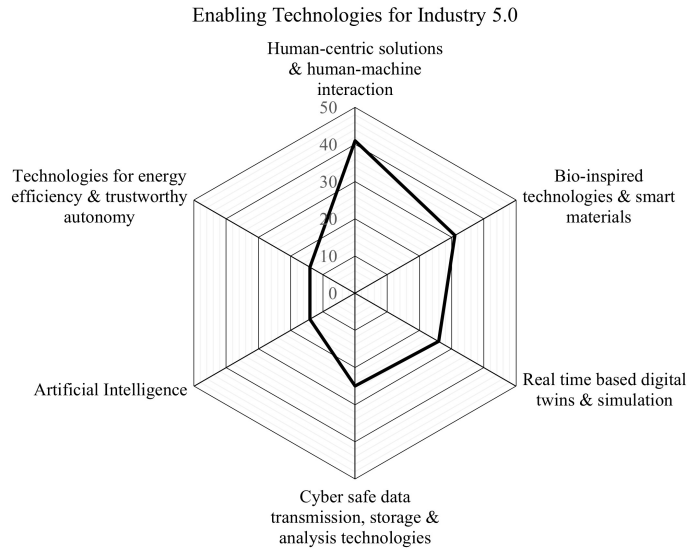
Focus	References
Causality-based and not-only correlation-based AI	/
Show relations and network effects outside of correlations	[36, 88, 46, 81, 47, 71, 73]
Ability to respond to new or unexpected conditions without human support	[87, 20, 70]
Swarm intelligence	/
Brain-machine interfaces	/
Individual, person-centric AI	[33, 73]
Informed deep learning	[58, 75, 25, 33, 73]
Skill matching of human and tasks	[25, 20, 70, 33]
Secure energy-efficiency AI	[75]
Ability to handle and find correlations among complex, interrelated data of different origin and scales in dynamic systems within a system of systems	[57, 58, 87, 20, 73]

**Table 12:** Technologies for energy efficiency & trustworthy autonomy

Focus	References
Integration of renewable energy sources	[52, 77]
Support of Hydrogen and Power-to-X technologies	/
Smart dust and energy autonomous sensors	/
Low energy data transmission and data analysis	[63, 65, 77, 39]

Figure 8 summarizes the research interest for each of the 6 axes of the technological enablers for Industry 5.0. It appears that the *Technologies for energy efficiency & trustworthy autonomy* is the least covered aspect, barely reaching 5 papers (7%). Then comes *Artificial Intelligence* and *Bio-inspired technologies & smart materials* axes, covered by respectively 15 (22%) and 17 (25%) papers. *Human-centric solutions & human-machine-interaction*, *Real time based digital twins*

*E* simulation, *Cyber safe data transmission, and storage* & *analysis technologies* axes are taking particular importance in the literature, being present in more than 30 out of the 68 papers (more than 44%). If it is not surprising to see the human aspect particularly standing out, since it is one of the main aspect of the search *R*, the fact that Digital Twins and real-time simulations-related technologies are taking an important place in research needs to be pointed out. Those are usually seen as ways to cope with emergent phenomenons within complex systems. Figure 8 shows that, what lies beneath Industry 5.0's technological enablers is in fact a search to deal with complex industrial systems, where both humans and industrial assets could be considered as one single socio-technical system.



**Figure 8:** Number of publications regarding the technological framework

## 6 Discussion

In this paper, a SLR questioning the place given to the human into current and future industrial systems, and more specifically regarding IoT and CPS developments, has been conducted. It has shown the great, recent, and collaborative international interest for the subject, but equally a certain lack of global vision. The retrieved papers have been analyzed through both a systemic and a technological framework, aiming to tackle a *Technology, Organization* and *Human* triptych [7]. This literature analysis has notably highlighted the existence of many IoT and CPS derivative, aimed at developing socio-technical systems and fostering more human-integrative systems. Regarding the systemic framework, and based on previous works [50], these approaches have been classified into 4 categories corresponding to the 4 types of socio-technical systems previously exposed, and presented by figure 9. If this figure, failing to present the actual date of appearance or importance of each of these variant (volumetry), is not suitable to present any conclusion, it can nonetheless be used as an aggregation basis for a further research.

To deepen the elements presented in this study, the Web of Science scientific database has been searched, for each of the IoT and CPS variant listed in table 2 and present in figure 9. For each

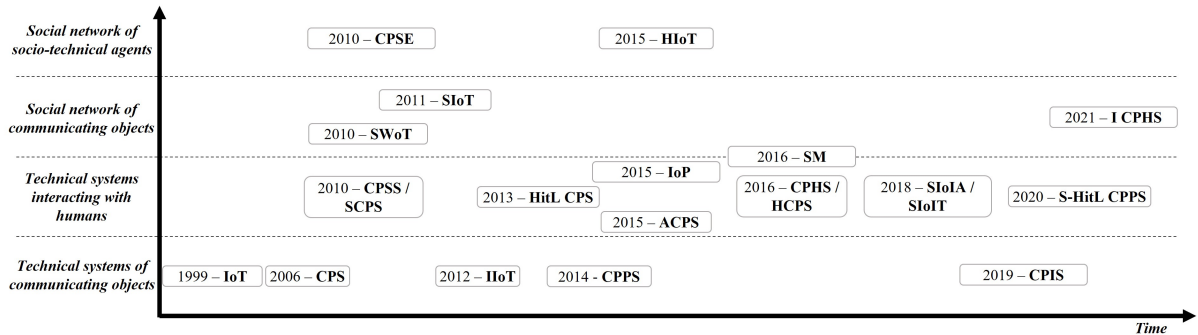


Figure 9: IoT and CPS variants’ distribution regarding the 4 types of socio-technical systems

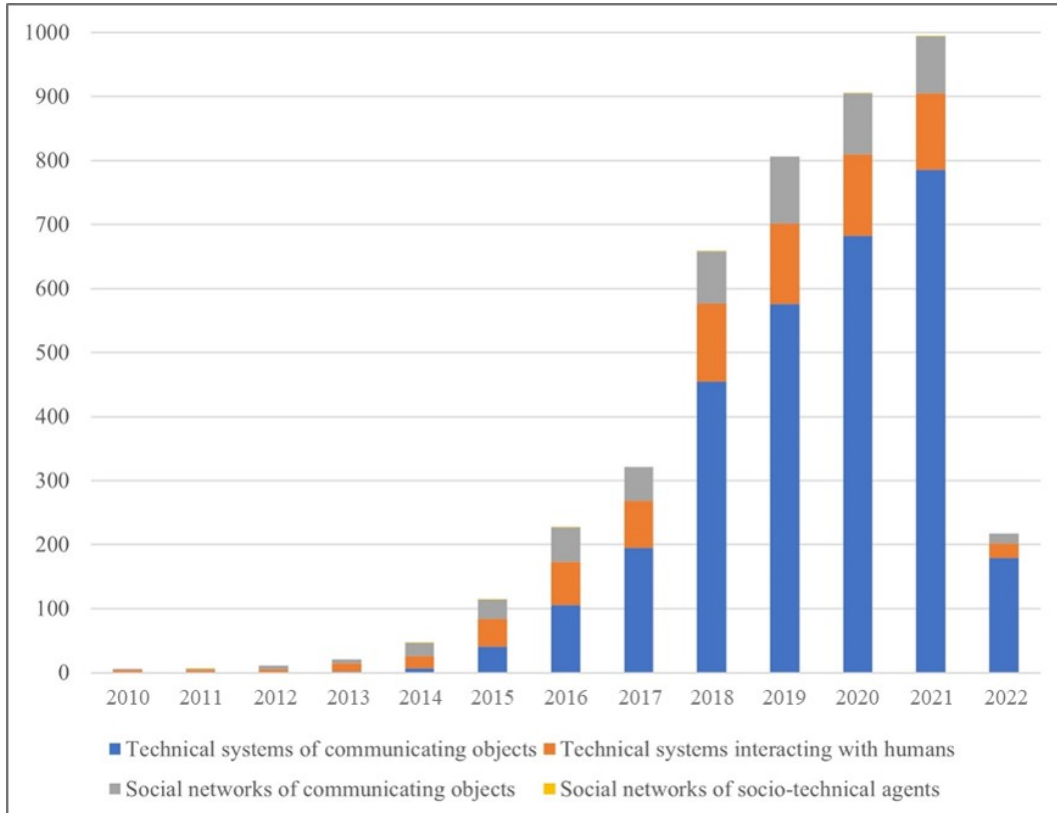
acronym presented here (except "IoT" and "CPS", which could be retrieved in any of these searches and therefore bias the results), the full-name of the approach has been exactly Title-Abstract-Keywords-searched, and the number of papers retrieved per year saved. Then The results have been grouped by type of socio-technical approach, as presented by figures 6 and 9. Results of this aggregated search are presented by figure 10. Overall, the recent and strong rise of these approaches in the literature is clearly observable there. Equally, what can be stated here is the clear dominance of broad technical approaches such as Industrial IoT (IIoT) or Cyber-Physical Production Systems (CPPS). Nonetheless, approaches focusing on the development of social networks of communicating objects, or human-system interaction systems, such as Social IoT or Social CPS, are significant. The social networking of socio-technical agents is hardly present though.

Besides, the technological framework showed that today’s human centric technologies were both support and enabling tools for a better consideration of the human and its variability (related to its physical or cognitive conditions). Notably, the omnipresence of embedded internet-connected devices coupled to the recent progresses of technologies such as new causal AI, explainable AI, Digital Twins, or Augmented/Virtual/Mixed reality, can be seen as a vectors of *tangibility* [99], making the system more understandable and thus more acceptable. Also, the bio-inspired technologies and smart materials, easing human-system inclusion, can be cited as example of promising advances. Those can either be taken as human-machine interaction enhancers, or decision-making supports, guaranteeing human integrity and well-being at work. Hence, these new technologies are not only making the concept of Human-Centered Design credible, but they equally constitute an acceptability vector for future IoT- and CPS-based systems and their developments. However, new issues and challenges are raised concerning data source management, for instance regarding security and respect for private life, impacting those technologies’ social acceptability and their adoption.

## 7 Conclusion

To conclude, this literature study has shown the great interest for human-centricity in today’s industrial research. Besides, what has been enlightened is that the development of actual socio-technical systems has to rely on the 4 grounding concepts of systemics: interactions, wholeness, organization, and complexity. By studying these concepts more closely, the authors have established a classification of socio-technical systems, from networks of communicating objects to social networks of socio-technical agents. Yet, even if many promising developments have been identified, the literature





**Figure 10:** Results per year for each of IoT and CPS variants into Web of Science, aggregated accordingly to their distribution regarding the 4 types of socio-technical systems

shows a clear predominance of the 2 human-system interfacing and social relationships' transposition to technical systems approaches. The research has stayed strongly focused on the development of technical devices and approaches for a better consideration of the human aspect into manufacturing systems. What seems to be lacking today is a generic framework within which these approaches can find their place, and that can be a basis for the development of future socio-technical systems.

Hence, enabling the consideration of future industrial systems as complex socio-technical ones, where both human and industrial assets would be considered as a coherent whole will require to bridge many gaps. Though, several leads can already be foreseen. From an engineering viewpoint, the raise of HSI as a full-fledged research field carries great potential to better integrate human, thanks to the convergence of both new technologies and multidisciplinary fields (complexity science, organizational theory, cognitive sciences, etc.). Another approach would be to design future systems as human mechatronic societies [100], or based on human societies schemes. This would start by identifying, defining, and formalizing the social relationships occurring within those to apply them to industrial assets [101].

As a conclusion, the limitations of this study should be discussed. This review could be used as a beginning for future researches, since some references have been filtered during SLR process. Therefore, by filtering differently with other criteria, with less focus on technological assets for example, this SLR study could be expanded to other dimensions. Moreover, papers dealing with

societal aspects such as governmental policies, ethics, or sustainable development found in the analyzed papers were not developed in this study. Yet, the deep changes that will be brought to manufacturing landscape by Industries 4.0 & 5.0's assets and technologies will inevitably have societal repercussions. To cope with this transition, factors such as workers' income, social security, skills and knowledge will have to be considered through participative, inclusive, and empowering work organizations which goes beyond the current vision of CPS and IoT based systems the study needs to be enlarged to other production paradigms like Lean Production Systems and their complexity [102].

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