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How the Technologies underlying Cyber-Physical Systems support the Reconfigurability Capability in Manufacturing. A Literature Review

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How the Technologies underlying Cyber-Physical Systems support the Reconfigurability Capability in Manufacturing. A Literature Review

Nowadays, manufacturing firms need the reconfigurability capability to be responsive in the current context characterized by unpredictable and frequent market changes and the reduction of product life cycle. Despite the relevance of the subject, a challenge for practitioners is the development of a strategy aimed to increase the level of reconfigurability with long-term goals of customization and responsiveness. Moreover, traditional manufacturing paradigms are disrupted by the transformation of manufacturing systems in Cyber-Physical Systems (CPS), thus introducing innovative means also to increase the level of reconfigurability in manufacturing systems. This study investigates what technologies underlying CPS support the reconfigurability capability and how these support the reconfigurability along system life cycle. Thus, the technologies underlying CPS are classified in seven categories and it is shown how they enable the sequence of utilization of the reconfigurability characteristics (modularity, integrability, diagnosability, scalability, convertibility and customization) along system life cycle. The results of the study can guide practitioners in developing reconfigurability as strategic capability. Moreover, different directions for future research can be considered, as discussed in the conclusions.

Keywords: Manufacturing System Life Cycle; Reconfigurability; Reconfigurability Characteristics; Cyber-Physical Systems; Industry 4.0; Digitalisation

1. Introduction

Unpredictable and frequent market changes and the sharp reduction of product life cycle challenge the competitiveness of manufacturing firms as they constantly need adequate levels of customization and responsiveness to face these business pressures (Gu and Koren 2022). For this reason, reconfigurability, which is the ability to repeatedly change the components of a manufacturing system in a cost-effective way (Rösiö 2012), is undoubtedly a desired capability for manufacturing firms (Shaik, Rao, and Rao 2015; Goyal, Jain, and Jain 2013; Bortolini et al. 2021; Campos Sabioni, Daaboul, and Le

Duigou 2021; Hashemi-Petroodi et al. 2020; Bi et al. 2008a). Accordingly, reconfigurability and reconfigurable manufacturing boost a flourishing research activity since the first introduction of the Reconfigurable Manufacturing Systems paradigm by Koren et al. (1999).

Despite that the theory on reconfigurable manufacturing systems has been consolidated over more than two decades, practitioners are still far from the concrete implementation of these systems in reality (Napoleone et al. 2020; Saliba et al. 2019; Rösiö et al. 2019).

One of the main challenges in moving towards reconfigurable manufacturing is the development of a strategy aimed to increase the level of reconfigurability through the definition of long-term goals, type and extent of changes needed, and required enablers (Boldt and Rösiö 2020). For what concerns the enablers, the ongoing 4th industrial revolution leads to new opportunities. Relying on the diffusion and exploitation of digital technologies in manufacturing systems, it is disrupting traditional manufacturing paradigms (ElMaraghy et al. 2021) and transforming current manufacturing systems into Cyber-Physical Systems (CPS) (Brettel et al. 2014; Penas et al. 2017; Xu, Xu, and Li 2018; Thoben, Wiesner, and Wuest 2017). CPS introduce innovative means valuable also to increase the level of reconfigurability in manufacturing systems (Leitao et al. 2015; Mazzolini et al. 2017).

Considering the system life cycle as a key concept to support the development of reconfigurability as strategic capability, this paper aims to investigate how CPS support the reconfigurability capability. Specifically, this study addresses the following research questions:

- *RQ1: "What technologies underlying CPS support the reconfigurability capability in manufacturing?"*

- *RQ2: "How the technologies underlying CPS support the reconfigurability capability along system life cycle?"*

1.1 Reconfigurability: a strategic capability

The manufacturing system life cycle is a relevant concept to describe reconfigurability as strategic capability. To this end, four stages of the manufacturing system life cycle – i.e. (i) the configuration, (ii) the ramp-up, (iii) the service life, and (iv) the reconfiguration of the system – can be introduced (see Figure 1). These are described below.

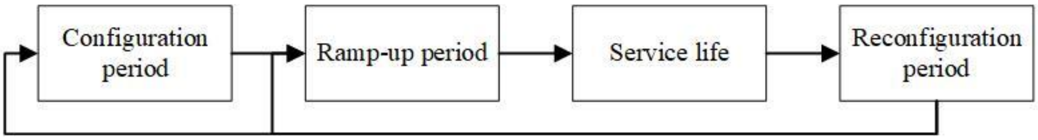

Figure 1 The four stages of the manufacturing system life cycle

Moreover, reconfigurability can be broken down to six characteristics: modularity, integrability, diagnosability, scalability, convertibility, and customization (Boldt and Rösiö 2020; Bi et al. 2008b; Andersen, Brunoe, and Nielsen 2015; Maganha, Silva, and Ferreira 2020). Customization refers to the ability to customize the system to be able to produce the required product family and can be seen as the change driver and trigger of the reconfigurability capability (Boldt and Rösiö 2020). Therefore, customization has a strategic role.

Referring to the manufacturing system life cycle, a "sequence of utilization" of the characteristics that allows achieving customization can be also introduced (Maganha, Silva, and Ferreira 2020; Napoleone, Pozzetti, and Macchi 2018; Boldt and Rösiö 2020; Singh et al. 2017).

- In the configuration period – i.e., the period for decisions on the structure of the system –, modularity and integrability are utilized, as they denote the system and components functionalities being separated into units with standard interfaces that can be easily combined, changed, and re-arranged (Andersen et al. 2019);

- In both the ramp-up period – i.e. the period for decisions to reach a stable production state –, and the service life of the system – i.e. the period for decisions to maintain a stable production state –, diagnosability is utilized. It allows (i) quick identification of the sources of quality and reliability problems (Mehrabi, Ulsoy, and Koren 2000; Liu et al. 2004) and (ii) quick correction of operational problems (Koren and Shpitalni 2010; Gumasta et al. 2011; Singh, Khilwani, and Tiwari 2007) within the manufacturing system;
- In the reconfiguration period – i.e., the period for decisions on system's adaptability to changes –, scalability and convertibility are utilized, as they directly relate to the manufacturing system's adaptability to changes: convertibility to changes in product mix (adapting system functionality) and scalability to changes in demand (adapting system capacity) (Maganha, Silva, and Ferreira 2018).

As a background, it is worth remarking the roadmap developed and empirically validated by Maganha, Silva, and Ferreira (2020). Their roadmap implements reconfigurability based on the sequence of the reconfigurability characteristics, to aid manufacturing firms in the development of reconfigurability in manufacturing. The empirical validation of the roadmap is particularly interesting to pave the way towards the implementation of reconfigurability as strategic capability.

1.2 Cyber-Physical Systems

Relying on the application of digital technologies, CPS in manufacturing are systems accomplishing the following functions:

- F1. data acquisition/collection (Thoben, Wiesner, and Wuest 2017; Dai et al. 2020);
- F2. data transmission and system communication (Thoben, Wiesner, and Wuest 2017; Dai et al. 2020);
- F3. data storage (Dai et al. 2020);
- F4. data analytics and knowledge extraction (Thoben, Wiesner, and Wuest 2017; Dai et al. 2020; Doltsinis et al. 2020);
- F5. monitoring of the manufacturing process (Dai et al. 2020).
- F6. visualisation and consultation of information (Dai et al. 2020; Doltsinis et al. 2020);
- F7. decision making (Dai et al. 2020; Doltsinis et al. 2020);
- F8. actuation/manipulation of the manufacturing process (Thoben, Wiesner, and Wuest 2017; Dai et al. 2020);

These general functions are also included in the traditional automation pyramid, where each of the functions refers to a specific level of the pyramid (see the reference standard for manufacturing firms ISO 2013). CPS add innovative aspects to the traditional automation pyramid: in these manufacturing systems – recurring to specific technologies – all the aforementioned functions can be potentially embedded into manufacturing processes (Ribeiro and Bjorkman 2018), thus processes become intelligent, leading to the decentralisation of the pyramid (Alcácer and Cruz-Machado 2019) and modularisation of such processes (Ribeiro and Bjorkman 2018).

The remainder is structured as follows: section 2 motivates the choice of literature review as methodology for this study and provides details on the research process. Section 3 illustrates the results of the literature review and the answers to the two research questions. Finally, section 4 outlines the contribution of this study for practitioners and academics and provides directions for future research.

2. Research methodology

The theory on reconfigurable manufacturing has been consolidated over years, while the theory on CPS is relatively more recent, anyhow its discussion is growing at an extreme pace.. This, together with the fact that CPS disrupt traditional manufacturing paradigms and introduce innovative means also to increase the level of reconfigurability in manufacturing systems, motivated the conduction of a structured literature review. To this regard, only few existing review articles have simultaneously investigated reconfigurable manufacturing and CPS (Bortolini, Galizia, and Mora 2018; Xia and Xi 2019; Ivanov et al. 2021; Morgan et al. 2021; Cardin 2021), and to the best of authors' knowledge, none of the available review articles aimed at analysing how technologies underlying CPS support the reconfigurability capability along the manufacturing system life cycle.

Therefore, the two research domains investigated in the present study are the technologies underlying CPS on the one hand, and the reconfigurability characteristics as main constituents of the reconfigurability capability along system life cycle on the other hand.

Taking into account the peculiarities of the operations management field compared to others, the guidelines provided by Durach, Kembro and Wieland (2017) were followed to conduct the structured literature review as detailed in the following subsections.

2.1 First step: literature search and preliminary analysis

In a first step, the sample of potentially relevant academic literature was identified. The search databases used for the investigation are Scopus and Web of Science. To ensure the coverage of the research questions and to intersect the CPS research domain with the reconfigurability research domain, the following five search strings were used:

- Search string 1 (to investigate the relationship between CPS and the modularity and integrability characteristics): “manufacturing” AND “cyber-physical system” AND (“Modularity” OR “integrability” OR “modular” OR “module”).
- Search string 2 (to investigate the relationship between CPS and the diagnosability characteristic): “manufacturing” AND “cyber-physical system” AND (“Diagnosability” OR “quality” OR “reliability” OR “diagnosis” OR “diagnostic”).
- Search string 3 (to investigate the relationship between CPS and the adaptability characteristic): “manufacturing” AND “cyber-physical system” AND (“Changeover” OR “scalability” OR “convertibility” OR “conversion” OR “adaptability” OR “adaptation” OR “adaptivity”).
- Search string 4 (to investigate the relationship between CPS and the customization characteristic): “manufacturing” AND “cyber-physical system” AND (“Customization” OR “personalisation” OR “individualisation”).
- Search string 5 (to ensure to reach any further relevant contribution): "manufacturing" AND ("cyber-physical system" OR "industry 4.0" OR "industrie 4.0" OR "smart manufacturing") AND ("reconfigurability" OR "reconfigurable").

To maintain the focus within the research boundaries, articles were filtered by title, abstract and keywords. Moreover, the pertinent literature was selected by applying appropriate inclusion and exclusion criteria to the identified sample, as detailed below.

- To ensure the high impact of the selected articles in terms of readership, only articles written in English language were reviewed.
- To increase the likelihood of identifying high quality articles, only journal articles were reviewed, leaving aside contributions such as magazine, conference and working papers.
- Finally, no time limitations were set, as literature on the application of CPS in manufacturing is relatively recent.

By applying these criteria, a set of 359 potentially relevant articles was reached. Due to the explosion of research interest in the CPS-related subject characterised by the massive use of keywords such as CPS, industry 4.0, and smart manufacturing, a careful preliminary analysis of the abstracts of the reached literature was conducted, aimed at screening the broad set of reached literature to identify the contributions strictly aligned with the purpose of the present study. Thus, 93 articles were excluded for being out of scope. After the preliminary screening, a search of the keywords related to reconfigurability characteristics (i.e. those included in the search strings) within the full text of these papers was done, aiming at identifying any section possibly referring to the reconfigurability characteristics. Among the 266 articles, those referring to any technology(ies) underlying CPS and, at the same time, one or more reconfigurability characteristics were identified. Any observation on the support of CPS to the reconfigurability characteristics was recorded on a database. Following this procedure, a total set of 128 articles was selected. The following table (Table 1) summarises the literature review process; it also reports whether the articles were reached taking outset in: (i) search string 1 (modularity and integrability); (ii) search string 2 (diagnosability); (iii) search string 3 (adaptability), (iv) search string 4 (customization); and (v) search string 5 (other relevant keywords). A few screened articles was identified in more than

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one of the aforementioned five search strings, for this reason the overall number of both screened and selected journal articles (reported in the first row of Table 1) is lower than the number obtained by calculating the summation of articles within individual search strings (reported in the remaining rows of Table 1).

Table 1 A synthesis of the literature review process

	Screened journal articles	**Selected journal articles**
Overall literature (all five search strings, removing duplicates)	**359**	**128**
Search string 1 (Modularity and Integrability)	60	19
Search string 2 (Diagnosability)	176	59
Search string 3 (Adaptability - Scalability and Convertibility)	67	36
Search string 4 (Customization)	54	23
Search string 5 (other relevant keywords)	68	Resorted, depending on addressed reconfigurability characteristics

2.2 Second step: literature coding and analysis

The 128 selected articles were coded in a database, reporting citation information. For each article, any observation on the support of any technology(ies) underling CPS to the reconfigurability characteristics was transcribed in the database as reported in the analysed articles. In this way, the technologies underlying CPS and supporting the reconfigurability capability were identified. Thus, these technologies were transcribed - as indicated in the analysed articles.

During the subsequent analysis, each of the transcribed technologies found in literature was classified based on the covered general functions within the list provided in section 1 (F1 to F8). Thus, technologies covering the same general functions were grouped together: seven classes of technologies underlying CPS and supporting the reconfigurability capability were identified, leading to an answer to the RQ1. For each of the so identified classes, details on enabled reconfigurability characteristics were added, based on the collective analysis of the observations transcribed in the database, leading to an answer to the RQ2. It is worth pointing out that the obtained classification is congenial to the objective of the present study, and that the identified technologies could be classified differently, according to other objectives and needs. To this regard, as the academic interest in CPS in manufacturing is relatively recent, multiple and occasionally divergent definitions of the analysed technologies have been provided in literature. The results of the analysis are described in section 3.

3. Results of the review

The RQ1 is answered in section 3.1, where the technologies underlying CPS that were mentioned as impacting the reconfigurability capability have been classified according to the eight functionalities of the automation pyramid, listed in section 1.2 (F1 to F8). The RQ2 is answered in section 3.2, where it is illustrated how the technologies underlying CPS support the reconfigurability capability along system lifecycle.

3.1 Technologies underlying CPS and covered general functions

The seven classes of technologies supporting the reconfigurability capability in manufacturing are: (i) T1. Sensor, measurement, and data acquisition technologies; (ii) T2. Communication and connectivity technologies, open and standard interfaces; (iii) T3. Edge, fog and cloud computing; (iv) T4. Simulation, artificial intelligence, and machine learning; (v) T5. Advanced monitoring, and digital twin; (vi) T6. Ubiquitous computing, assistance systems, augmented and virtual reality, and human-machine interfaces; (vii) T7. Decentralised control architecture. These (T1 to T7) are described in this section. As shown in Table 2, each of these seven technologies covers at least one of the general functions (F1 to F8).

Table 2 Classes of technologies underlying CPS based on covered general functions

Technologies	*General functions (F1 to F8)*
T1	F1. data acquisition/ collection.
T2	F2. data transmission and system communication.
T3	F2. data transmission and system communication; F3. data storage; F4. data analytics and knowledge extraction.
T4	F3. data storage; F4. data analytics and knowledge extraction.
T5	F5. monitoring of the manufacturing process; F6. visualisation and consultation of information; F7. decision making.
T6	F6. visualisation and consultation of information; F7. decision making; F8. actuation/ manipulation of the manufacturing process.
T7	F8. actuation/ manipulation of the manufacturing process.

3.1.1 T1. Sensor, measurement, and data acquisition technologies

T1 covers data acquisition/collection (F1) through sensors (Li et al. 2019), measurement (Xu and Hua 2017) and data acquisition (Peres et al. 2018) technologies. For example, depending on specific objectives and corresponding needed types of data, appropriate sensors should be selected, such as: vibration sensors to monitor motor or spindle vibration, sound sensors to monitor the noise in the process, thermal sensors to monitor the temperature of coolant (Li et al. 2019).

Data acquisition within T1 technologies spans from the field data coming from the manufacturing system to the external data at other levels, such as order data, or planning and supervisory data. This is in alignment with the decentralization of the automation pyramid discussed in section 1.2 (see also section 3.1.7).

3.1.2 T2. Communication and connectivity technologies, middleware, open and standard interfaces

T2 covers data transmission and system communication (F2). Components of the CPS are connected through communications networks (Abdi et al. 2018), it is relevant that

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communication and connectivity technologies enable managing heterogeneous information coming from different manufacturing systems or components (Jaskó et al. 2020); interactions should allow manufacturing systems to share and exchange information among multiple domains (Abid et al. 2015). An industrial manufacturing middleware is used as an integration platform to enable the communication between various components, thus allowing highly heterogeneous subsystems to effectively interoperate (García-Valls et al. 2017; Gosewehr et al. 2017). Providing a standardized way to communicate, the middleware makes both an easy vertical and horizontal communication possible. The fact that all the different manufacturing components involved in CPS have to interoperate also rises hardware requirements (García-Valls et al. 2017) and, to this end, equipment should have open and standard interfaces (Ribeiro and Bjorkman 2018) so that manufacturing systems can be constructed in a plug-and-work manner, thus aggregating predefined components such as robots and conveyors (Otto, Vogel-Heuser, and Niggemann 2018).

3.1.3 T3. Cloud, fog, and edge computing

T3 covers data transmission and system communication functionalities (F2), as in the case of T2; T3 also covers data storage (F3), and data analytics and knowledge extraction (F4). Specifically, data storage is particularly relevant (Shafiq, Szczerbicki, and Sanin 2018) as manufacturing systems become data-intensive environments (Thoben, Wiesner, and Wuest 2017), also due to the availability of inexpensive sensors (Kammerer et al. 2020).

Cloud (Dalmarco et al. 2019), fog (Caggiano et al. 2020) and edge (Keung et al. 2020) computing offer data storage (F3) and data analytics (F4) capabilities. Moreover, acting in different layers, these three technologies also offer communication (F2) capabilities (He et al. 2020), thus allowing the communication between these layers and enabling decentralised decision-making and reliable real-time control (O'Donovan et al. 2018). Finally, cloud, fog and edge layers could be the locations in which knowledge extraction (F4) happens; indeed, these layers could host reasoning and learning algorithms to extract new knowledge for prediction models (Villalonga et al. 2020) such as machines' conditions and operations' sequences for products (Wan et al. 2019).

Cloud computing, relying on internet-based big data analytics, is the enabling technology when data need to be collected from socialised and distributed resources and then, exploiting shared big data analytics, analysed to promptly react to disturbances and unexpected events (Ding and Jiang 2018). Cloud computing is the aggregation of computing as a utility and software as a service, where the applications are delivered as services over the Internet. Although cloud computing can support distributed engineering scenarios, intelligence and processing (e.g. decision-making) typically remain central, which means distributed clients depend on consistent and resilient connections with the cloud; therefore, these centralised services are not suited to the control architecture needed for decentralised and autonomous decision-making (O'Donovan et al. 2018). As explained below, acting on different layers, fog and edge computing complement cloud computing and overcome this limitation.

Fog computing aims at offering data processing and storage capabilities closer to the end devices. At the fog layer, small-scale cloud functionality is ensured by the so-called fog nodes, i.e. devices with computing, storage, and network connectivity, thus improving efficiency and performance and reducing the amount of data transmitted to the cloud for processing, analysis and storage, hence reducing network traffic and latency (Caggiano et al. 2020).

Edge computing implements features such as networking, computing, storage, and application at the network edge near a device or data source (Keung et al. 2020).

Providing a variety of services at the source of data, edge computing can greatly relieve the pressure of network bandwidth and data processing of a cloud environment. At the same time, it reduces transmission delay, greatly improving the response speed and reliability of services (Yin et al. 2020). In an edge computing infrastructure, huge amounts of raw sensor data can be pre-processed and transmitted to the subsequent fog and cloud layers (Kammerer et al. 2020; Thramboulidis, Vachtsevanou, and Kontou 2019).

3.1.4 T4. Simulation, artificial intelligence, machine learning

T4 covers data storage (F3) and data analytics and knowledge extraction (F4).

In CPS, individual manufacturing components should be provided with computation modules capable of extracting data from the shop-floor and of elaborating them in order to assess possible deviations, acting accordingly (Peres et al. 2018). Simulation is also a way of evaluating a proposed system for various parameters within a specific period of time; it is the imitation of the operation of the real-world process or system over time (Polenghi, Fumagalli, and Roda 2018).

Intelligent behaviours, such as learning and reasoning before making decisions, are carried out typically by using artificial intelligence (Tran et al. 2019). For example, applying machine learning techniques is relevant to this end. Machine learning can be defined as a system’s capacity to improve its performance on a given task or set of tasks over time based on previous results. Machine learning models are an example of advanced predictive analytics (O’Donovan et al. 2018). Artificial intelligence also supports the knowledge extraction (F4) by providing reasoning capabilities and data-driven analytics capabilities based on, for example, reinforcement learning- and evolutionary algorithms, as shown in Villalonga et al. (2020).

3.1.5 T5. Advanced monitoring, digital twin

T5 covers monitoring of the manufacturing process (F5), visualisation and consultation of information (F6), and, eventually, decision making (F7). Moreover, to provide relevant information and knowledge to decision making, T5 needs to be fed with technologies covering the function of data analytics and knowledge extraction (F4), including artificial intelligence and simulation environments.

Cyber and physical modules can be coordinated by tracking the progress of the life cycle activities, thus allowing different stakeholders to be aware of the overall progress of the cyber physical activities (Cecil et al. 2019). When decision making (F7) is an embedded function of T5, automatic decisions can be made. Otherwise, relevant users can be alerted in order to make correct decisions, for example when structural changes (insertion, removal, or modification) occur along with system evolution (Iglesias, Sagardui and Arellano 2019). A digital twin links and integrates the physical world with the cyber world of computation, by allowing reliable real-time virtualization of physical production units as well as real-time feedback from the virtual model to the physical world (Wang et al. 2019; Jakovljevic, Vidosav, and Stojadinovic 2017). It provides a complete digital footprint of a physical system from design and development through the end of the product life cycle. Thus, it may not only be used for modelling of systems during the system development to support design or to validate system properties, but also can support the operations and manufacturing for optimised operations and failure prediction (Wang et al. 2019).

3.1.6 T6. Ubiquitous computing, assistance systems, augmented and virtual reality, human-machine interfaces

T6 covers visualisation and consultation of information (F6), decision making (F7) and actuation/manipulation of the manufacturing process (F8).

Ubiquitous computing is a concept in computer science in which computing is performed at any location (Chen and Tsai 2017). However, in manufacturing having computational capability (F4) at any location is not affordable. For this reason, ubiquitous manufacturing typically implies that manufacturing services can be ubiquitously provided (also thanks to the data transmission and system communication (F2) function, included in T2 and T3) (Chen and Tsai 2017). Ubiquitous manufacturing is related to the availability of management, control and operation functions of manufacturing systems anywhere, anytime, using direct control, notebooks, or handheld devices (assistance systems) that provide ubiquity of functions (Barenji et al. 2020). Thus, analysed data (F4) can be provided in the form of services, for example: (i) to indicate the performance of the process (F6); (ii) to optimise maintenance plans (F7); and (iii) to correct eventual process faults (F8) (Li et al. 2019). Assistance systems can support both design (Engel, Greiner, and Seifert 2018) and operations (Krugh and Mears 2018) of CPS. Augmented and virtual reality technologies make assistance systems user-friendly and improve users' experience, thus improving the effectiveness of training and operational activities (Tao et al. 2019; Marin and Brîndașu 2014; Dalmarco et al. 2019). Regarding manual operational activities, next generation of feedback to humans includes incorporating smart and augmented reality wearables to enhance timely notification of events and to improve the quality of products (Krugh and Mears 2018). For machining operations, human-machine interfaces and personal digital assistants (such as smartphones) can be used for interfacing machines with workers (Tran et al. 2019).

3.1.7 T7. Decentralised control architecture

A decentralised control architecture enables the actuation/manipulation of the manufacturing process function (F8) of CPS, but, as detailed below, it refers to the whole automation solution, and thus it generally enables all CPS functions.

Traditional automation solutions create static, monolithic and strongly hierarchical logical bounds between all the components of manufacturing systems (integral design) (Ribeiro and Bjorkman 2018). Decentralisation implies that the overall system should contain the needed logic to ensure aspects such as the joining/removal of individual components and the functional correctness of the manufacturing system (García-Valls et al. 2017). It requires overcoming the traditional automation pyramid described in the ISA-95 international standard, on the one hand; and, on the other hand, overcoming the variety of machine-to-machine (M2M) communication standards coupled with proprietary software (Morgan and O'Donnell 2017). Control decentralisation ensures autonomy, but the more decentralised the control strategy is, the more difficult it is to adapt it to current industrial equipment (Ribeiro and Bjorkman 2018).

Different streams of literature have addressed T7 with different technology views, some examples are reported below.

- A service-oriented architecture is a set of architectural tenets for building autonomous yet interoperable systems, it specifies that distributed resources should provide their functionalities in the form of services that can be dynamically discovered and accessed through asynchronous messaging by exposing its interface (Morgan and O'Donnell 2017).
- A layered architecture with global and local control layers supports reconfigurability (Chen et al. 2020) through the separation between functionalities aimed at the support of activities within a single manufacturing system (e.g. time critical human-robot collaboration) and functionalities aimed at synchronizing activities across multiple systems (Erasmus et al. 2018).

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- A multi-agent system is composed of multiple interacting agents (Blesing et al. 2017). In this concept, real-time manufacturing information can be timely shared and components' manufacturing capabilities are exposed to the industrial network as manufacturing services (Zhang et al. 2017).

3.2 Technologies underlying CPS and the reconfigurability capability along system life cycle

This section details how the technologies underlying CPS support the reconfigurability capability along system lifecycle. To this end, the following Table 3 reports a summary of the typical challenges associated to different reconfigurability characteristics and periods of the manufacturing system life cycle and summarises the technologies underlying CPS which, according to literature, support manufacturing firms to address those challenges.

The number of papers that mention a specific CPS technology for a specific reconfigurability characteristics is indicated (last row of the table).

Table 3 Reconfigurability capability, typical challenges and enabling technologies along system life cycle

<table>
<tr><td></td><td colspan="28">Reconfigurability capability (sequence of utilization of the reconfigurability characteristics)</td></tr>
<tr><td>Required characteristics</td><td colspan="7">Modularity and integrability</td><td colspan="7">Diagnosability</td><td colspan="7">Adaptability (scalability and convertibility)</td><td colspan="7">Customization</td></tr>
<tr><td>Period of the system life cycle</td><td colspan="7">Configuration period</td><td colspan="7">Ramp-up period and service life</td><td colspan="7">Reconfiguration period</td><td colspan="7">(Change driver)</td></tr>
<tr><td>Typical challenges</td><td colspan="7">• Quick and cost-effective integration of modules
• Quick and cost-effective integration of interfaces</td><td colspan="7">• Quality problems
• Reliability problems/ Machine failures</td><td colspan="7">• Capacity adaptation
• Functionality adaptation</td><td colspan="7">• Customized and evolving market requirements
• Unpredictable market requirements
• Responsiveness and productivity</td></tr>
<tr><td rowspan="2">Enabling technologies Summary of literature</td><td>T1</td><td>T2</td><td>T3</td><td>T4</td><td>T5</td><td>T6</td><td>T7</td><td>T1</td><td>T2</td><td>T3</td><td>T4</td><td>T5</td><td>T6</td><td>T7</td><td>T1</td><td>T2</td><td>T3</td><td>T4</td><td>T5</td><td>T6</td><td>T7</td><td>T1</td><td>T2</td><td>T3</td><td>T4</td><td>T5</td><td>T6</td><td>T7</td></tr>
<tr><td>0</td><td>16</td><td>9</td><td>9</td><td>3</td><td>1</td><td>7</td><td>21</td><td>20</td><td>17</td><td>36</td><td>16</td><td>16</td><td>11</td><td>6</td><td>17</td><td>12</td><td>19</td><td>13</td><td>11</td><td>14</td><td>7</td><td>13</td><td>12</td><td>9</td><td>7</td><td>6</td><td>15</td></tr>
</table>

As shown in Table 3, the seven classes of technologies underlying CPS (T1 to T7) impact in different ways the reconfigurability capability, based on the sequence of utilization of the characteristics of reconfigurability along system life cycle.

Next subsections detail the results summarised in Table 3 and present representative examples from literature that may offer guidance to map the role of each technology along system life cycle, this supports the development of a strategy aimed to improve the reconfigurability capability with long-term goals of customization and responsiveness. The overall classification of literature from where the representative examples are taken is reported in the appended tables 4, 5, 6 and 7.

3.2.1 T1 and reconfigurability capability

As summarised in Table 3, existing literature has particularly discerned that T1 (sensor, measurement, and data acquisition technologies) support diagnosability, thus it allows effective management of quality and reliability problems during system ramp-up and service life. Indeed, T1 technologies offer the field data that are of utmost importance for monitoring the current situation and timely detecting deviations from a desired performance or abnormal behaviours. The representative examples from literature are reported as follows.

During the ramp-up and service life, diagnosability is ensured through data streaming from reliable sensors and other data sources. These provide CPS with data that feed their reactions to unexpected events (Scholze, Barata, and Stokic 2017) such as machine failures (Kammerer et al. 2020) and quality issues (Chen et al. 2019) along the manufacturing processes.

In the reconfiguration period, T1 technologies are also needed to sense and describe the status of resources, supporting their adaptability (De Miranda et al. 2020; Song et al. 2021b).

From a strategic perspective, T1 technologies, with both status data of low-level sensors as well as data acquired from the external environment such as demand or product data, triggers data-driven customization of configurations (Wan et al. 2019).

In general, T1 technologies support the sequence of utilization of the reconfigurability characteristics along system life cycle, as these technologies provide essential information to: (i) outline system configuration and virtually describe the modules of the system in the configuration period, (ii) ensure responsiveness during the ramp-up and service life, and (iii) identify the new requirements for the reconfiguration period.

3.2.2 T2 and reconfigurability capability

As summarised in Table 3, existing literature has discerned that T2 (communication and connectivity technologies, middleware, open and standard interfaces) support all reconfigurability characteristics. With regard to diagnosability and customization, literature has often treated T2 in association with T3 as they both cover the data transmission and system communication (F2) function (see Table 2), while T3 adds the data storage (F3) and data analytics and knowledge extraction (F4). The representative examples from literature are reported as follows.

In the configuration period, CPS are constructed in a plug-and-work manner, aggregating predefined system components, thus ensuring modularity and integrability (Otto, Vogel-Heuser, and Niggemann 2018). In openly operating manufacturing systems, industrial equipment can be integrated almost instantly to tackle specific production needs and can be disconnected and moved to another location once the production targets have been fulfilled (Ribeiro and Bjorkman 2018). For example, open-architecture machine tools, comprising a fixed standard platform and various individualized modules that can be added and rapidly swapped, allow engineers to continuously reconfigure the manufacturing system (Leng et al. 2020b). The integrability of physical systems and components is supported by formal resource models describing resources' capabilities and by ontologies capturing the semantics necessary to ensure interoperability (Jaskó et al. 2020). The coupling of system components with other components despite the high heterogeneity is also simplified by the embedment of service-orientation into the design of system components (Harrison, Vera, and Ahmad 2016). To this end, standardization of service interfaces and plug-and-work principles make the manufacturing system not only highly modular, but also dynamically adjustable at any 'point of interest' – while continuing production (Weyer et al. 2016).

During the ramp-up and service life, CPS allow collaborative interactions that trigger prompt reactions to unexpected events such as machine failures (Chen et al. 2020), by combining sensor measurements of different local attributes, allowing achieving more complete information (Olsen and Tomlin 2020).

In the reconfiguration period, the introduction of interoperable devices with ever changing architecture allows building manufacturing systems that are highly adaptable to ever changing market requirements (Jakovljevic, Mitrovic, and Ivanova 2017). The use of middleware technology is relevant as communication backbone to enable dynamic and temporary participation in the manufacturing CPS of high numbers of heterogeneous components (opening the door for higher adaptability levels) (García-Valls et al. 2017).

From a strategic perspective, customization is supported because thanks to T2 a CPS allows manufacturing components to collaborate towards new configurations required to manufacture newly designed products (Tran et al. 2019).

In general, T2 technologies support the sequence of utilization of the reconfigurability characteristics along system life cycle, as they support: (i) the integration of heterogeneous modules in the configuration period, (ii) the combination and exploitation of heterogeneous information during the ramp-up and service life, and (iii) the integration of new modules in the reconfiguration period.

3.2.3 T3 and reconfigurability capability

As summarised in Table 3, existing literature has discerned that T3 (cloud, fog, and edge computing) support all reconfigurability characteristics. Regarding diagnosability, literature has often treated T3 in association with T4 as they both cover the data analytics and knowledge extraction (F4) function (see Table 2). The representative examples from literature are reported as follows.

In the configuration period, operating in different layers, cloud, fog and edge computing allow the implementation of a modular architecture (Chen et al. 2020), where heterogeneous manufacturing systems can be rapidly modelled and configured in a simple way (Jiang et al. 2020). Moreover, the transmission of data (F2) among layers enables the functional independence of the manufacturing systems. Indeed, cloud computing enables on-demand access to services and resources, shifting manufacturing resources into shared services that can be accessed based on plug-and-work mechanisms (Barenji et al. 2020). Moreover, fog and edge computing allow the provision of “micro” services – closer to end devices – thus associated to manufacturing resources’ functionalities (He et al. 2020; Jiang et al. 2020). These micro services have characteristics such as standardisation, modularisation, and reusability, and can be stored in software libraries (Chen et al. 2020).

During the ramp-up and service life, data analytics and processing capabilities (F4) allow the definition of failures’ causes and the prediction of equipment’ degradation processes (Li et al. 2019). The computational capability (F4) of CPS also assist in preventing the propagation of anomalies and returning the manufacturing systems to their normal operation conditions, either via self-adjustment mechanisms or alerts triggering human intervention (Peres et al. 2018). Moreover, the extraction of knowledge from existing data and information triggers data-driven reconfigurations (Wan et al. 2019)

In the reconfiguration period, as T3 technologies enable autonomous and collaborative behaviours, it opens the way to improved adaptability (Shalini and Kumaravel 2019) and customization (Huang et al. 2020) of manufacturing CPS. Indeed, CPS have self-configuring features to deal with changes and the boundaries of their components evolve over time (Penas et al. 2017). Moreover, the coupling of device network (F2) and computing (F4) capabilities, enables the control and execution of services – representing distributed manufacturing resources and capabilities – to meet prevailing manufacturing conditions and requirements (Adamson, Wang, and Moore 2019).

From a strategic perspective, customization is supported because T3 technologies enable the activation of data-driven reconfigurations according to shop-floor conditions and market trends (Wan et al. 2019).

In general, T3 technologies support the sequence of utilization of the reconfigurability characteristics along system life cycle, as they determine: (i) the software hierarchy ensuring the modularity of components in the configuration period, (ii) the service orientation during the ramp-up and service life, and (iii) the collaboration among distributed resources in the reconfiguration period.

3.2.4 T4 and reconfigurability capability

As summarised in Table 3, existing literature has discerned that T4 (simulation, artificial intelligence, machine learning) support all reconfigurability characteristics. With regard to modularity and integrability, literature has often treated T4 in association with T3 since they both cover the data analytics and knowledge extraction (F4) function (see Table 2), moreover the F4 function of both T4 and T3, enabling local computational capabilities, has often been treated in association with T7. The representative examples from literature are reported as follows.

In the configuration period, the fact that distributed resources have computation capabilities (F4) make them potentially independent from a functional perspective (Morgan and O'Donnell 2018). Indeed, distributed computational capability (modularity and integrability) supports local decision making, thus allowing to respond quickly to specific requirements (Lee, Ryu, and Cho 2017a). Conversely, when individual components are not functionally independent, but are part of production processes making use of one or several of their functions, any change might involve larger sections of manufacturing systems instead of specific modules (Ribeiro and Bjorkman 2018) with lower response times.

During the ramp-up and service life, Machine learning allows building intelligent CPS capable to identify failures and adapt to ever-changing production conditions (Carvajal Soto, Tavakolizadeh and Gyulai 2019).

In the reconfiguration period, the adaptability of modular CPS is enabled by the use of simulation tools, intended to support (re-) engineering processes, to evaluate the impact of external and internal changes and to react in a timely manner to critical influences on production management (Weyer et al. 2016). Simulation tools are relevant because they support in predicting future states from historical data, thus enabling physical evolution of systems over time (O'Donovan et al. 2018).

During the ramp-up, the service life and in the reconfiguration period, knowledge extraction is also at the basis of the self-awareness capabilities, based on a learn, reason, act cycle. Self-awareness is the foundation of the self-X properties (self-configuration, -healing, -optimization, -protection, -adaptiveness) which are core for automated reconfiguration of production systems (Goetzinger et al. 2020).

From a strategic perspective, customization is supported because by leveraging on big data analytics, artificial intelligence and machine learning, T4 technologies allow converting social data regarding products and their functionalities generated by customers into product engineered features and corresponding manufacturing processes (Ding and Jiang 2018; Kokuryo et al. 2017).

In general, T4 technologies support the sequence of utilization of the reconfigurability characteristics along system life cycle, as they support: (i) the software modularity (thus intelligence) of components in the configuration period, (ii) their self-X properties during the ramp-up and service life and, (iii) the prediction, simulation of new requirements and self-adaptiveness in the reconfiguration period.

3.2.5 T5 and reconfigurability capability

As summarised in Table 3, existing literature has particularly discerned that T5 (advanced monitoring, digital twin) support diagnosability and adaptability. The representative examples from literature are reported as follows.

In the configuration period, T5 technologies describe available physical modules and their range of capabilities/skills (both the currently implemented and the potential extensions) (Gašpar et al. 2020).

During the ramp-up and service life, T5 technologies not only provide a digital representation of the physical world, but its dynamic representation over time (Lanza, Haefner, and Kraemer 2015). This offers the opportunity to generate and use critical quality data (Colledani et al. 2018) and reliability data (Lanza, Haefner, and Kraemer 2015) along the manufacturing processes and to adapt the production system accordingly, increasing the diagnosability of the system. Indeed, the dynamic representation of manufacturing processes enables operations managers to uncover previously unknown relationships between manufacturing system conditions and outcomes, thus driving continuous improvement in defect and downtime reduction (Olsen and Tomlin 2020).

In the reconfiguration period, by establishing cyber-physical connection via digital twin models, various manufacturing resources can be formed as dynamic autonomous system to co-create personalised products (Leng et al. 2019), thus in the end supporting a higher degree of adaptability and customization.

From a strategic perspective, customization is supported as T5 technologies assist the designer of the manufacturing system in evaluating the operational performance of new configurations (Song et al. 2021b).

In general, T5 technologies support the sequence of utilization of the reconfigurability characteristics along system life cycle, as they allow to: (i) outline system configuration and virtually describe the modules of the system, (ii) support the validation of system properties during the ramp-up and service life, and (iii) visualise the effect of new requirements in the reconfiguration period.

3.2.6 T6 and reconfigurability capability

As summarised in Table 3, existing literature has particularly discerned that T6 (ubiquitous computing, assistance systems, augmented and virtual reality, human-machine interfaces) support diagnosability and adaptability. The representative examples from literature are reported as follows.

During the ramp-up and service life, T6 technologies enable the diagnosability of CPS, especially in case of manual manufacturing operations. Training and assistant systems that are aware of workers' states can provide active guidance to the worker as needed, thus helping workers learning desired skills, reduce the rate of rejects, and guarantee the product quality (Tao et al. 2019). By integrating the physical process with useful details regarding the process itself, augmented reality can simplify the job to workers, avoiding mistakes and improving quality (Marin and Brîndașu 2014). Augmented Reality provides the possibility of real-time consultation, whenever information is necessary for a certain task execution, thus improving training and conditions of work, allowing employees to learn their procedures in-site, reducing the learning curve and decreasing errors in the execution of tasks (Dalmarco et al. 2019). With regard to machining operations, human-machine interfaces could provide operators with real-time guidance services, which could greatly reduce the chance of quality defects caused by improper operations or wrong installations of materials (Zhang et al. 2017). For example, diagnosis on tool conditions (i.e. wear over the life cycle and expected breakage occurrence) can be offered as services (Caggiano 2018).

In the reconfiguration period, T6 technologies support the adaptability characteristic during product and process design. The exploitation of knowledge-based assistance systems enables an automatic inference of technical requirements. Indeed, assistance systems could provide the required knowledge to support the selection and combination of process modules and networked services to reduce the complexity during the engineering process: an engineer would then need to deal less with technical details (automatically determined) and could predominantly focus on the design of the actual product to be produced (Engel, Greiner, and Seifert 2018). Taking for example the design of assembly systems, assembly resources (such as workers) can be represented as entities exposing their properties and functionalities as cyber-physical services. This simplifies the design of the systems and supports its automation, thus allowing dynamic reconfiguration of processes according to specific market requirements (Thramboulidis, Kontou, and Vachtsevanou 2018). During manufacturing operations, augmented reality enables for example increased adaptability in workers in executing new tasks as well as training by means of virtual simulation of manufacturing processes (Posada et al. 2015).

From a strategic perspective, customization is enabled by T6 technologies, for example human-computer-machine interfaces, allowing the visualization and validation of internal and external changes, support the self-adaptation of the manufacturing system and its existing resources to new configurations (Martinez et al. 2021).

In general, T6 technologies support the sequence of utilization of the reconfigurability characteristics along system life cycle, as they provide: (i) the accessibility to modules' properties in the configuration period, (ii) the required- and service oriented- support during the ramp-up and service life, and (iii) the support to the definition of new features or the implementation of new capabilities in the reconfiguration period.

3.2.7 T7 and reconfigurability capability

As summarised in Table 3, existing literature has particularly discerned that T7 (decentralised control architecture) supports diagnosability, adaptability and customisation. However, literature has often treated T7 in association with T3 and T4 (as they both cover the data analytics and knowledge extraction (F4) function), and therefore emphasizing the support of this combination of technologies to all reconfigurability characteristics. The representative examples from literature are reported as follows.

In the configuration period, the transition from traditional monolithic control architectures – which have an integral design – to decentralised ones enables the modularity, autonomy and coordination of system components (Fumagalli et al. 2018). The traditional integral design does not enable modularity and integrability because, in case of reconfigurations, it enlarges the scope of action, misaligning it with the one of the physical components (Ribeiro and Bjorkman 2018); on the other hand, a properly designed decentralised control architecture not only enables the functional independence of system components, but also allows the control of heterogeneous technologies within the manufacturing system (Erasmus et al. 2018). Meaningful examples of this are proposed by (Morgan and O'Donnell 2018), which also highlight the role of intelligence (thus recalling the T3 and T4 technologies) to build local and potentially independent functional modules to achieve a high degree of system modularity.

During the ramp-up and service life, a decentralised control architecture also supports the diagnosability characteristic. The CPS is capable to self-configure itself, thus addressing any disturbance, such as machines failures, along the manufacturing processes (Shalini and Kumaravel 2019; Ko, Kim, and Park 2016; Barenji et al. 2019). For example, on the basis of the diagnosis on tool conditions, a local server might activate the proper corrective action to be taken, such as tool replacement, process halting or parameters change, sending the right command to the machine tool control (Caggiano 2018).

In the reconfiguration period, decentralised and autonomous manufacturing units enable a high degree of adaptability to changing surrounding conditions through inbuilt flexibility and autonomy (Lass and Gronau 2020; Otto, Vogel-Heuser, and Niggemann 2018; Zhang et al. 2017). For example, in a product-driven multi-agent system, the product itself shares relevant information about itself with other components of the system thus enabling process adaptation to new requirements (Mihoubi et al. 2020). Multi-agent technologies provide self-organizing and self-adaptive mechanisms. Real-time manufacturing information can be timely shared and components' manufacturing capabilities are exposed to the industrial network as manufacturing services: through the data transmission and system communication (F2) function – realized, for example, by means of the internet - these can be discovered as potential resources to undertake specific manufacturing tasks (Zhang et al. 2017).

From a strategic perspective, customization is enabled because a manufacturing CPS based on distributed architectures, such as a multi-agent system, allows realising self-adaptation to evolving customized market requirements (Marin and Dan Brîndaşu 2015). The multi-agent technology allows self-adaptation of manufacturing processes based on product configuration (Leitão et al. 2015). In this sense, also the customization characteristic of manufacturing systems is improved.

In general, T7 technologies support the sequence of utilization of the reconfigurability characteristics along system life cycle, as they allow: (i) the modularity and autonomy of components in the configuration period, (ii) reactive and autonomous mechanisms during the ramp-up and service life, and (iii) autonomous adaptation to new requirements in the reconfiguration period.

4. Conclusions

In this study, based on a literature review, a classification of the technologies underlying CPS has been proposed, and their support to the reconfigurability characteristics in different periods of the manufacturing system life cycle has been discussed. To investigate reconfigurability as strategic capability, four stages of the life cycle – i.e. (i) the configuration, (ii) the ramp-up, (iii) the service life, and (iv) the reconfiguration – have been considered.

The theoretical contribution of this study lies in the comprehensive analysis of the support of the technologies underlying CPS to the reconfigurability capability along the manufacturing system life cycle. As documented in this study, the potentialities of CPS for reconfigurable manufacturing have been often pointed out by recent literature but, to the best of the authors' knowledge, there is no previous study that systematizes this knowledge. Among the stages of system life cycle, the service life appears particularly relevant when simultaneously investigating the two research domains of reconfigurable manufacturing and CPS. Indeed, during the service life, information and knowledge are built from extant operations of the manufacturing system, while the resident capabilities of the system are used before a new reconfiguration is timely triggered when needs arise. Moreover, the study shows that the technologies underlying CPS are particularly beneficial during the ramp-up and service life of the system (as they support diagnosability), this is extremely relevant considering that, from a strategic perspective, the reconfigurability capability along system life cycle implies several loops between ramp-up, service life and reconfiguration (Figure 1).

This study has industrial implications as it can guide practitioners in the development of a strategy aimed to improve the reconfigurability capability with long-term goals to face the challenges of unpredictable, customized and evolving market requirements in a cost-effective and responsive way, which is one of the main challenges in moving towards the implementation of reconfigurable manufacturing. The study also shows how the technologies underlying CPS support practitioners to address the typical challenges associated to different stages of the manufacturing system life cycle. These challenges have different conjugations, depending on the specific period of the manufacturing system life cycle. Quick and cost-effective integration of modules and/or interfaces are typical challenges of the configuration period, while quality and reliability problems are typical challenges of the ramp-up and service life periods. Finally, capacity and functionality adaptation are typical challenges of the reconfiguration period. All these different challenges find solutions in the seven classes of technologies underlying CPS, to this end section 3.2 reports representative examples from literature that may offer guidance to map the role of each technology along system life cycle.

Different directions of research can be undertaken based on this study because, showing relationships between characteristics and technologies along the manufacturing system life cycle, the classification can inspire research on both the design and the operation of reconfigurable CPS-based manufacturing systems. Moreover, while in available literature the reconfigurability characteristics have been widely investigated from a rather conceptual perspective, the provided classification directs to technological enablers of these characteristics, in their capability to address the challenges arising along the system life cycle. Finally, the classification can inspire research aimed to investigate the extent of the relationships between the identified classes of technologies and the reconfigurability characteristics. Future research aimed at quantifying the degree of reconfigurability of manufacturing systems can be based on this theoretical analysis, such as methodologies to quantify the level of reconfigurability of a manufacturing system or to quantify the reconfigurability potential that may be incorporated in manufacturing systems by implementing CPS technologies.

Another possible future research opened by this work is the implementation of more empirical research studies. To this end, case studies, surveys, and the collection of experts' opinions operating in manufacturing could be valuable to both validate the theoretical conclusions of this paper and to progress in one of the suggested future research directions. It is believed that empirical research would be valuable also because the digitalisation of manufacturing systems is an ongoing phenomenon: manufacturing firms are currently investing in digital technologies as these are already commercially available and practitioners and experts are able to provide valuable insights for the research in this field.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, [A.N.], upon reasonable request.

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Appendix

Table 4 Classes of technologies enabling modularity and integrability according to literature

Technologies	*Modularity and Integrability*
T2	(Gašpar et al. 2020; Maganha, Silva, and Ferreira 2020; Mantravadi et al. 2020; Prist et al. 2020; Wang et al. 2016; Chen et al. 2020; Erasmus et al. 2018; Harrison, Vera, and Ahmad 2016; Jaskó et al. 2020; Jiang et al. 2020; Lee, Ryu, and Cho 2017a; Leng et al. 2020b; Morgan and O'Donnell 2018; Otto, Vogel-Heuser, and Niggemann 2018; Ribeiro and Bjorkman 2018)
T3	(Chen et al. 2020; Erasmus et al. 2018; Lee, Ryu, and Cho 2017b; Leng et al. 2020b; Morgan and O'Donnell 2018; Ribeiro and Bjorkman 2018; Mantravadi et al. 2020; Nikolakis et al. 2020; W. Xu et al. 2021)
T4	(Chen et al. 2020; Garetti, Fumagalli, and Negri 2015; Lee, Ryu, and Cho 2017b; Leng et al. 2020b; Morgan and O'Donnell 2018; Ribeiro and Bjorkman 2018; Gašpar et al. 2020; Prist et al. 2020; Villalonga et al. 2021)
T5	(Gašpar et al. 2020; Villalonga et al. 2021; Abidi, Alkhalefah, and Umer 2021)
T6	(Villalonga et al. 2021)
T7	(Chen et al. 2020; Erasmus et al. 2018; Leng et al. 2020b; Morgan and O'Donnell 2018; Ribeiro and Bjorkman 2018; Brad, Murar, and Brad 2018; Villalonga et al. 2021)

Table 5 Classes of technologies enabling diagnosability according to literature

Technologies	*Diagnosability*
T1	(Caggiano 2018; Cai et al. 2016; Castaño et al. 2019; Chen et al. 2019; Cheng 2018; Colledani et al. 2018; Doltsinis et al. 2020; Götzinger et al. 2020; Kammerer et al. 2020; Keung et al. 2020; Lanza, Haefner, and Kraemer 2015; Nannapaneni et al. 2020; Peres et al. 2018; Scholze, Barata, and Stokic 2017; Siafara et al. 2018; Tao et al. 2019; Wang et al. 2019; Wang et al. 2018; Azamfirei, Granlund, and Lagrosen 2021; Bampoula et al. 2021; Stoj 2021)
T2	(Adrita et al. 2020; Al-Jaroodi, Mohamed, and Jawhar 2018; Barenji et al. 2019; Caggiano et al. 2020; Cai et al. 2016; Colledani et al. 2018; Dalmarco et al. 2019; Nannapaneni et al. 2020; Penas et al. 2017; Peres et al. 2018; Saez et al. 2020; Shalini and Kumaravel 2019; Siafara et al. 2018; Wang et al. 2019; Xing 2014; Yin et al. 2020; Stoj 2021; Tang et al. 2020; Song et al. 2021a)
T3	(Al-Jaroodi, Mohamed, and Jawhar 2018; Caggiano 2018; Caggiano et al. 2020; Castaño et al. 2019; Dalmarco et al. 2019; Keung et al. 2020; Lee 2017; Lee et al. 2018; Li et al. 2019; Nannapaneni et al. 2020; O'Donovan et al. 2018; Yin, Bao, and Zhang 2019; Yin et al. 2020; Azamfirei, Granlund, and Lagrosen 2021; Epureanu et al. 2020; Tang et al. 2020)
T4	(Adrita et al. 2020; Ahmed et al. 2021; Caggiano 2018; Cai et al. 2016; Carvajal Soto, Tavakolizadeh, and Gyulai 2019; Chen et al. 2019; Colledani et al. 2018; Dalmarco et al. 2019; Doltsinis et al. 2020; Götzinger et al. 2020; Huang, Badurdeen, and Jawahir 2018; Khorasgani, Jung, and Biswas 2015; Lanza, Haefner, and Kraemer 2015; Lee et al. 2018; Nannapaneni et al. 2020; O'Donovan et al. 2018; Peres et al. 2018; Rubio et al. 2019; Scholze, Barata, and Stokic 2017; Siafara et al. 2018; Tao et al. 2019; Tsai and Ko 2017; Upasani et al. 2017; Urbina Coronado et al. 2018; Wang et al. 2018; Wang et al. 2019; Peres, Azevedo, et al. 2021; Shin, Cho, and Oh 2018; Stoj 2021; Amini and Chang 2020; Azamfirei, Granlund, and Lagrosen 2021; Bampoula et al. 2021; Epureanu et al. 2020; Li and Niggemann 2021; Maganha, Silva, and Ferreira 2020; Peres, Guedes, et al. 2021)
T5	(Caggiano 2018; Iglesias, Sagardui, and Arellano 2019; Keung et al. 2020; Lanza, Haefner, and Kraemer 2015; Lee et al. 2018; Nannapaneni et al. 2020; Siafara et al. 2018; Tarallo et al. 2018; Tsai and Ko 2017; Urbina Coronado et al. 2018; Wang et al. 2019; Amini and Chang 2020; Azamfirei, Granlund, and Lagrosen 2021; Song et al. 2021a; Tang et al. 2020; Glatt et al. 2021)

T6	(Al-Jaroodi, Mohamed, and Jawhar 2018; Caggiano 2018; Cheng 2018; Colledani et al. 2018; Dalmarco et al. 2019; Doltsinis et al. 2020; Huang et al. 2018; Iglesias, Sagardui, and Arellano 2019; Krugh and Mears 2018; Peres et al. 2018; Siafara et al. 2018; Tao et al. 2019; Tarallo et al. 2018; Wang et al. 2018; Song et al. 2021a; Tang et al. 2020)
T7	(Barenji et al. 2019; Götzinger et al. 2020; Khorasgani, Biswas, and Jung 2019; Ko, Kim, and Park 2016; O'Donovan et al. 2018; Penas et al. 2017; Shalini and Kumaravel 2019; Siafara et al. 2018; Upasani et al. 2017; Boccella et al. 2020; Tang et al. 2020)

Table 6 Classes of technologies enabling adaptability according to literature

Technologies	*Adaptability*
T1	(Alexopoulos, Nikolakis, and Chryssolouris 2020; Mihoubi et al. 2020; De Miranda et al. 2020; Song et al. 2021b; Tuominen 2016; Zhang et al. 2021)
T2	(Alexopoulos, Nikolakis, and Chryssolouris 2020; Bohács and Rinkács 2017; Dalmarco et al. 2019; García-Valls et al. 2017; Jakovljevic, Vidosav, and Stojadinovic 2017; Lass and Gronau 2020; Liu, Jiang, and Zhang 2018; Marrella, Mecella, and Sardiña 2018; Mihoubi et al. 2020; Mostl et al. 2018; Pérez et al. 2020; Szász 2020; Barenji et al. 2020; Zhang et al. 2017; Beregi et al. 2021; De Miranda et al. 2020; Song et al. 2021b)
T3	(Adamson, Wang, and Moore 2019; Dalmarco et al. 2019; Jakovljevic, Vidosav, and Stojadinovic 2017; Lovas et al. 2018; Morgan and O'Donnell 2017b; Mostl et al. 2018; O'Donovan et al. 2018; Pérez et al. 2020; Barenji et al. 2020; Villalonga et al. 2020; De Miranda et al. 2020; Lee et al. 2020)
T4	(Alexopoulos, Nikolakis, and Chryssolouris 2020; Bohács and Rinkács 2017; Dalmarco et al. 2019; Huang et al. 2018; Lovas et al. 2018; Marrella, Mecella, and Sardiña 2018; Morgan and O'Donnell 2017b; Mostl et al. 2018; O'Donovan et al. 2018; Pérez et al. 2020; Villalonga et al. 2020; Zhang et al. 2017; De Miranda et al. 2020; Khan, Ghafoor, and Zahid 2021; Lee et al. 2020; Liu, Zhang, and Pannek 2019; Park 2017; Song et al. 2021b; Z. Bi et al. 2021)
T5	(Alexopoulos, Nikolakis, and Chryssolouris 2020; Bohács and Rinkács 2017; Harrison, Vera, and Ahmad 2016; Morgan and O'Donnell 2017b; Pérez et al. 2020; Zhang et al. 2017; Beregi et al. 2021; De Miranda et al. 2020; Lee et al. 2020; Liu, Zhang, and Pannek 2019; Maganha, Silva, and Ferreira 2020; Song et al. 2021b; C. Zhang et al. 2021)
T6	(Dalmarco et al. 2019; Engel, Greiner, and Seifert 2018; Huang et al. 2018; Krugh and Mears 2018; Marrella, Mecella, and Sardiña 2018; Pérez et al. 2020; Barenji et al. 2020; De Miranda et al. 2020; Maganha, Silva, and Ferreira 2020; Song et al. 2021b; Tuominen 2016)
T7	(Adamson, Wang, and Moore 2019; Alexopoulos, Nikolakis, and Chryssolouris 2020; Cruz Salazar et al. 2019; Jakovljevic, Vidosav, and Stojadinovic 2017; Lass and Gronau 2020; Mihoubi et al. 2020; Morgan and O'Donnell 2017b; O'Donovan et al. 2018; Villalonga et al. 2020; Zhang et al. 2017; Brad, Murar, and Brad 2018; De Miranda et al. 2020; Park 2017; Song et al. 2021b)

Table 7 Classes of technologies enabling customization according to literature

Technologies	*Customization*
T1	(Ding and Jiang 2018; Huang et al. 2020; Leng et al. 2020b; Marin and Brîndașu 2014; Kukreja, Manu, and Lawrence 2021; Vachálek et al. 2021; Wan et al. 2019)
T2	(Ding and Jiang 2018; Huang et al. 2020; Jakovljevic, Vidosav, and Stojadinovic 2017; Leng et al. 2020b; Liu et al. 2019; Marin and Brîndașu 2014; Ocker et al. 2019; Thramboulidis, Vachtsevanou, and Kontou 2019; Wan et al. 2018; Zheng et al. 2019; Kukreja, Manu, and Lawrence 2021; Wan et al. 2019; Wang et al. 2016)
T3	(Ding and Jiang 2018; Grassi et al. 2020; Jakovljevic, Vidosav, and

	Stojadinovic 2017; Kokuryo et al. 2017; Leitão et al. 2015a; Leng et al. 2020a; Thramboulidis, Vachtsevanou, and Kontou 2019; Wan et al. 2018; Zheng et al. 2019; Wan et al. 2019; Zhang et al. 2019; Zhou et al. 2021)
T4	(Ding and Jiang 2018; Leitão et al. 2015a; Leng et al. 2020a; Leng et al. 2019; Liu et al. 2019; Marin and Brîndașu 2014; Kukreja, Manu, and Lawrence 2021; Vachálek et al. 2021; Zhou et al. 2021)
T5	(Ding and Jiang 2018; Leng et al. 2019; Liu et al. 2019; Grassi et al. 2020; Maganha, Silva, and Ferreira 2020; Martinez et al. 2021; Vachálek et al. 2021)
T6	(Ding and Jiang 2018; Leitão et al. 2015b; Marin and Brîndașu 2014; Thramboulidis, Vachtsevanou, and Kontou 2019; Maganha, Silva, and Ferreira 2020; Martinez et al. 2021)
T7	(Ding and Jiang 2018; Grassi et al. 2020; Huang et al. 2020; Jakovljevic, Vidosav, and Stojadinovic 2017; Kokuryo et al. 2017; Leitão et al. 2015a; Leng et al. 2020a; Leng et al. 2019; Liu et al. 2019; Marin and Brîndașu 2014; Rareș Lucian Marin and Dan Brîndașu 2015; Ocker et al. 2019; Thramboulidis, Vachtsevanou, and Kontou 2019; Wan et al. 2019; Zhou et al. 2021)