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ORIGINAL ARTICLE

A maturity model for the autonomy of manufacturing systems

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Abstract

Modern manufacturing has to cope with dynamic and changing circumstances. Market fluctuations, the effects caused by unpredictable material shortages, highly variable product demand, and worker availability all require system robustness, flexibility, and resilience. To adapt to these new requirements, manufacturers should consider investigating, investing in, and implementing system autonomy. Autonomy is being adopted in multiple industrial contexts, but divergences arise when formalizing the concept of autonomous systems. To develop an implementation of autonomous manufacturing systems, it is essential to specify what autonomy means, how autonomous manufacturing systems are different from other autonomous systems, and how autonomous manufacturing systems are identified and achieved through the main features and enabling technologies. With a comprehensive literature review, this paper provides a definition of autonomy in the manufacturing context, infers the features of autonomy from different engineering domains, and presents a five-level model of autonomy — associated with maturity levels for the features — to ensure the complete identification and evaluation of autonomous manufacturing systems. The paper also presents the evaluation of a real autonomous system that serves as a use-case and a validation of the model.

Keywords Decision-making · Self-learning · Manufacturing · Digital twin · Industry 4.0 · Machine learning

1 Introduction

Modern manufacturing requires systems able to rapidly react to changes in production to meet the demands of the market. Short product life cycles, combined with decreasing batch sizes and increasing product variants, are challenging traditional production systems [1, 2]. Current conventional methods cannot handle the required changes, unpredictable events, and disturbances in a productive, cost-effective manner [3]. To help manage these dynamic challenges, the industrial concept of Industry 4.0 has emerged [4].

The improved decision-making enabled by Industry 4.0 typically lies with the operators, and production experts managing the system based on increased access to data and information about the system. Autonomy can be broadly defined as the ability and independence of a system to make decisions by itself [3]: in the context of a manufacturing system, autonomy is the ability of humans, robots, or software to achieve their goals without any external support [5]. This definition is often confused with the concept of automated systems that are designed to independently perform tasks and process local information without human intervention, but do not take complex decisions and are not able to respond to new situations [6].

Autonomy implementation in manufacturing is hindered by the lack of universal consistency in the detailed definition, its features, and how they are qualified. This work aims to uniquely define autonomy in the manufacturing context as a framework for both industry and research, with these steps.

1. Presenting and analyzing previous work related to autonomy definitions in different engineering and industrial contexts.

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2. Defining common features of autonomy from analysis of different systems.
3. Applying a Capability Maturity Model to the features to identify the level of maturity.
4. Harmonizing these features into a five-stage model of autonomous manufacturing.
5. Applying this five-stage model to a real use case.

Maturity models have been extensively used and applied to many knowledge areas. The pioneers were models developed in the software field. They introduce Capability Maturity Models (CMMs) [7], that then evolved into the Capability Maturity Model Integration (CMMI). These models can be used to describe a variety of phenomena such as organization, product life cycles, and change management. They are also applied to the manufacturing field [8]. In this work, we utilize the concept to create a connection between maturity of the identified features and possibility of autonomy in the system.

The rest of the paper is organized as follows: Section 2 analyzes background works related to autonomous systems in other engineering fields; Section 3 presents the developed model for classification and evaluation of autonomous systems; Section 4 introduces a real autonomous system as validation of the model; and finally, Section 5 discusses conclusions and further works.

2 Background

The word “Autonomy” is found in many engineering domains. Automated devices execute actions by a set of rules to produce an outcome, with minimum human intervention [9]. Autonomous individuals (commonly human workers) exhibit higher intelligence and flexible behavior, making them required for these situations that is why autonomy is one step beyond automation [10]. The key discriminator is the ability of an autonomous entity to face unanticipated situations and adapt its course of action to meet the challenges [11]. The closer an entity approaches full autonomy, the smaller the role of any external agent will be. In the specific case of humans, this could be a two-edged sword: as the system grows more independent and reliable, the less aware and prepared the operator would be to take over control, which is a critical barrier to autonomy [12]. The word “autonomy” in manufacturing has several meanings.

- The capability of individual entities to act and collaborate for achieving a specific goal without external influence [13].
- The capability of a system to control the execution of its plans and strategies [1].
- The capability of a system to recover without modifying scheduling [5].
- The ability of an entity to structure its own action and environment independently and without unwanted influence from outside [14].
- The ability of a system to make its own decisions and to act on its own, and to do both without direct human intervention [15].

Recent technological developments (e.g., autonomous cars, unmanned aerial vehicles, and artificial intelligence) raised critical concerns about the extent to which autonomy should be developed, and the same concern applies to the participation of autonomous entities in production systems [10]. Defining the upper limits of autonomy in intelligent systems is a complex task, where the challenge is to develop an autonomous system in which a human operator would still be able to regain control in exceptional situations [16]. This is a key reason why a high-level definition of autonomy in manufacturing is necessary. Without detail on the subcomponents that create autonomy, autonomy can neither be effectively implemented component-by-component nor can it be controlled to maintain quality and safety.

2.1 Autonomy in other engineering domains

Understanding the challenges in the domains where autonomy is at the forefront of technological development is critical to understanding autonomy in manufacturing, combined with the enabling technologies and methodologies. The available literature — including grey literature — that is presented in this section will be used to build a definition of autonomy for manufacturing.

Unmanned vehicles — Unmanned vehicles are a significant application area for autonomy [17]. Fully self-driving cars are gaining interest, and purchasing cars with high degrees of autonomy is now possible [18]. The potential impact of autonomous cars on public safety is an emotive subject, and there are large volumes of research in the area [19]. SAE International’s model of autonomy levels [20] is one of the most widely cited and important enablers of discussion of self-driving cars, showing the importance of such a model.

In addition to ground vehicles, autonomous aerial vehicles are being used for a wide range of applications including inspection [21], search and rescue [22], goods delivery [23], and military applications [24].

Autonomous robots — Robotics is a broad area covering industrial, consumer (such as automated vacuum cleaners), disaster response, and humanoid devices. Robots are highly flexible, and autonomy allows them to respond to a variety of problems. A common approach for autonomous robotic control is multi-agent systems [25]: each agent has a belief-desire-intention (BDI) software architecture and is responsible for its goals as a "desire" and coordinates with other agents to achieve it [26]. As many robots are battery-powered, autonomous robotic research includes energy use optimization [27].

Autonomous maintenance — Forcomplex and variable maintenance tasks in non-optimal environments, autonomy may be required to enable the devices to respond to new situations. Fully autonomous robots can perform maintenance tasks without help and can detect cracks along pipe infrastructures [28]. Aircraft oil delivery tube crack detection also uses autonomous robots for routine inspection of fatigue cracking [29]. Robotic appliances also have applications in other high-power, high-consumption applications [30, 31].

Autonomous manufacturing — Industry 4.0 has increased the adoption of connectivity and data sharing on the shop floor, which lays the groundwork for autonomy [32]. The rise of modular, flexible, and reconfigurable manufacturing systems has led to further developments in intelligent solutions for distributed autonomy such as holonic manufacturing [33], and the autonomous adaption of manufacturing systems to unexpected changes [34]. Autonomy in the process industry helps sustaining the effectiveness of continuous process [35] despite variation and uncertainty in the supply chain [36]. However, the degree of autonomy applied in most manufacturing enterprises is low; a lack of a common understanding of what autonomy means and how it would affect manufacturing processes is a hurdle that needs to be overcome.

Autonomous quality — Quality systems have been an early success story of autonomy and the application of AI in manufacturing [37], with machine vision [38], tool wear [39], and ability to adapt to changing situations. Machine vision integrated with quality control has a significant impact in traditional go/no go quality checking scenarios [40]. Modern quality systems are increasingly utilizing autonomous infrastructures to maintain strict Statistical Process and Quality Control (SPQC) — the more advanced the level of autonomy, the more predictive quality control in the production process can be performed. The earlier the quality control is performed, the fewer parts will need to be scrapped or fixed, improving productivity and process stability [41, 42].

2.2 Enabling methodologies and technologies

Autonomy is a concept enabled by multiple technologies in conjunction. In the same way that machine learning was defined in the 1950s [43], but only recently gained mainstream attention due to the improvement in the computing technologies that enable it, autonomy is a mature concept, intrinsically tied to the enabling technologies hereby described.

The human role in autonomous systems — Human intelligence and its contribution remain pivotal to autonomous systems because of safety, security, and bias issues: keeping humans informed, enabling consent, and offering scope for intervention gives effectiveness to the system and respects ethics [13].

A high level of autonomy should not imply the exclusion of humans, but allows for seamless integration. This leads to higher levels of collaboration to achieve the common key performance indicators [44, 45].

Table 1 Summary of the main existing models that inspired the present work

Model	Field	Levels	Notes
SAE International J3016 [20]	Autonomous vehicles	6 levels	Standard driving automation model
Schegner et al. [60]	Process industry	—	Definition of autonomy focused on plant operators
Gamer et al. [6]	Process industry	6 levels	Taxonomy of autonomous key features
RB MAL [59]	Manufacturing systems	6 levels	I. Degree of automation
RB MAL [59]	Manufacturing systems	6 levels	II. Degree of control intelligence
Thomson et al. [63]	Manufacturing systems	3 levels	System development, ecosystem configuration, business model design
Bauer et al. [61]	Manufacturing systems	5 levels	Manufacturing systems features connection with maturity
Styr et al. [62]	Manufacturing systems	4 levels	More detailed description of the levels of autonomy

Self-X capabilities — Self-X abilities define the expected autonomous behavior and generally comprise four major characteristics: self-configuration, -healing, -optimization, and -protection, known as self-CHOP capabilities.

1. Self-configuration: the ability of a system to reconfigure [46, 47], to adapt automatically to environmental changes [48], and to automatically install, configure, and integrate new software components [49].
2. Self-healing: the ability to automatically detect and diagnose faults, react to disruptions, and repair where possible with the objective of maximizing availability, maintainability, and reliability [46, 48, 49].
3. Self-optimization: the ability to measure current performance against the known optimum in reactive and proactive ways [46, 49], and maximize resource allocation and utilization [48].
4. Self-protection: the ability to establish trust [48], detect, identify, and protect against disruptions, damage, or attacks [46]. The system uses early-warning sensing systems to anticipate and prevent system-wide failures [50].

Internet of things — The objective of autonomous control is to keep the productivity of the system high, even when responding to dynamic situations. Machine autonomy is typically based on decision-making informed by raw data that is turned into valuable information [51]. The collection of the data is supported by the Internet of Things (IoT) concept [52], and the related concept of the Industrial Internet of Things (IIoT).

Artificial intelligence and machine learning — A key technology for high performance in manufacturing systems is artificial intelligence (AI) [53–55]. AI has been applied for many years, but more modern applications based on machine learning (ML) enable intelligence to be applied to highly complex situations, finding patterns in data without the need for a pre-specified model.

Distributed intelligence — Improved system intelligence and the use of IoT lends itself to integrating more computing power into systems. This concept of "edge computing" allows data to be processed closer to the source, which is essential when data volumes are large [56]. The implementation of distributed intelligence in smart systems is also enabled by the use of Multi-Agent Systems (MAS) [25, 57]. Each "intelligent agent" represents the capabilities and goals of manufacturing processing units [58], and the agents collectively work towards achieving overall system goals.

2.3 Existing models and their levels of autonomy

Manufacturing is not the only domain for which autonomy is a key research area, and existing models of autonomy have been created to understand how autonomy can be achieved and where gaps needs to be filled.

Therefore, we collected and summarize in Table 1 the main models that developed from similar industries, such as automotive [59], and the derived process industry models [6, 60]; also, we listed the models from the manufacturing world that inspired the present work, the main being Bauer et al. [61], who developed a five maturity levels model of manufacturing system features, with an extension from Styr et al. [62], who argued for a more detailed description of the autonomy levels.

From the list of references emerges the need for a thorough work of collection, characterization, and classification of an expanded set of main features constituting an autonomous manufacturing system. Moreover, this work aims to provide a detailed description of the levels of maturity that the features can reach, and to describe five separated levels of autonomy in a model that will be validated with a use-case example. With this model, a lead evaluator can assess the maturity in autonomy of the single features in a manufacturing system and visualize where the biggest effort should be put to improve it.

3 Model of autonomous systems features

In Section 2, we presented the main research trends under investigation, and several engineering applications with autonomy, to give an overview of the predominant, essential features to define and implement autonomy. We summarized those features in Table 2, listing the characteristics that were extracted from the evaluation of the literature from Section 2, based on what gives manufacturing systems intelligence, and autonomy capabilities. Some of the features are re-named and combined to better comply with the existing research literature on manufacturing autonomy. Every feature is assigned to its specific category, and functionalities are added to each of them, for clarity reasons.

The existing literature on autonomy highlights the desired outcome: independent intelligence. However, there is a lack of standards and frameworks to define whole-system autonomy, and defining a correct implementation is a difficult problem to address.

By expanding the "degree of automation" concept [59], we present a five-level model of autonomy to describe and characterize system-wide autonomy and enable the evaluation of an entire manufacturing system.

Table 2 Categories, features, and functionalities for the model

Category	Feature	Functionality
I. Data, information, and knowledge	Data	Data structure
		Data processing
		Data integration
	Knowledge management	Knowledge management
	Interoperability	Hardware, software, and knowledge
II. Process	Synchronization	Material/logistics
		Physical (Production Machines)
	Optimization	Optimization function Productive and Unproductive contribution
	Reliability	Failure recovery
III. Interactions	Context-aware	Physical, virtual, and user environment
	With humans	Operation
		Programming
		Control
	Safety	Integration level
IV. Infrastructure	Connectivity	Types of network
		Application levels
	Industry control	Control Technology development
		Application levels
	Cybersecurity	Hardware, software, and knowledge
V. Self-X	Self-configuration	Monitoring, learning, patterning
	Self-healing	Diagnosis, stabilization, repair
	Self-optimization	Reflection, regulation, structuring
	Self-protection	Monitoring, control
VI. Measurement performance	Accuracy	Precision
		Repeatability
		Sensitivity
	Stability	Transferability
	Certainty	Calibration

- *Autonomous Level 1 (AL1)*: Factory without autonomy.
  Manufacturing systems with the lowest autonomy level. The systems rely on operator actions and decisions, and general systems are not connected together or have any centralized control other than the operator.
- *Autonomous Level 2 (AL2)*: Basic automated factory.
  The inclusion of centralized control in connected systems allows for improved levels of automation and some context-aware features. Human operators are still needed to intervene for many tasks.
- *Autonomous Level 3 (AL3)*: Adaptable factory.
  Introduces self-adaptable behaviors and predictive features to meet unpredictable events. Human operators receive suggestions for optimized activities, but the main system tasks are still under human control, either directly or via a centralized control system. Collected data is continuously monitored and automatically shared between all connected systems.
- *Autonomous Level 4 (AL4)*: Semi-autonomous factory.
  The system defines its own course of action based on high levels of context-awareness, within established boundaries. Human operators work cooperatively with the system. Even if the system is able to analyze its environment for "business as usual" execution, system goals and the response to major disturbances are still monitored by humans.
- *Autonomous Level 5 (AL5)*: Fully autonomous factory.
  The system is fully self-adaptable to uncertain or unforeseen inputs, enabled by advanced self-learning capabilities. The system is able to choose the best option to meet common goals for connected manufacturing systems without human intervention, even in the face of new and unforeseen challenges.

The combined Autonomous Level of a system starts with the maturity levels of the constituent features, defined in the following subsections [61]. The use of the model allows the identification and evaluation of the manufacturing system's autonomy capabilities based on the features' level of technological maturity, as well as identifying where a low maturity level is holding back the overall system autonomy.

The grading system in this section is based on the evaluation of the characteristics giving manufacturing systems intelligence and autonomy. Those were drawn from an analysis of literature and practical examples, as presented in Section 2, and were analyzed by the pool of authors to formulate a gradation system that would apply to the general system. In the following subsections, we present the grading for each individual category.

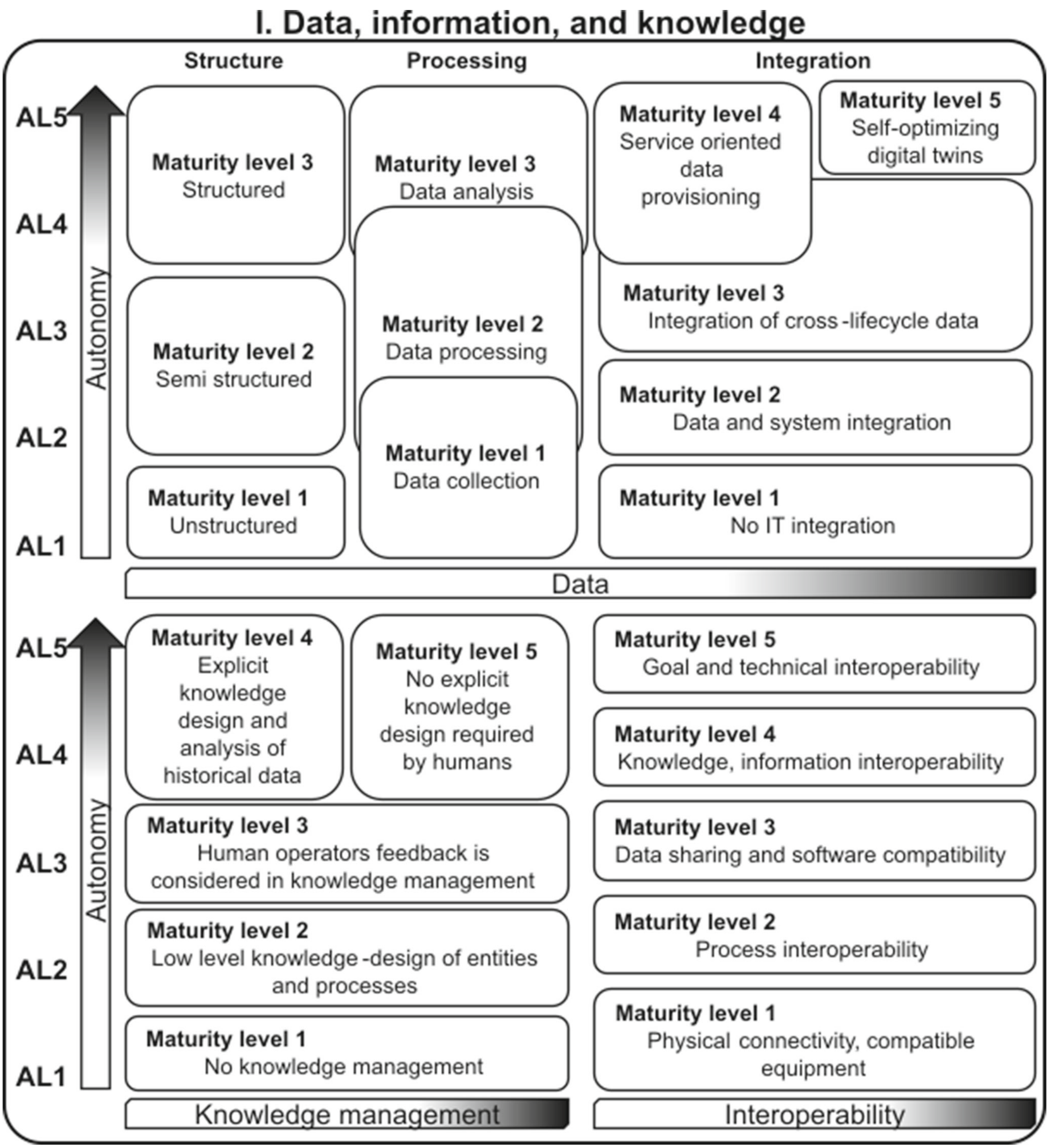

Fig. 1 Maturity levels of category I. Data, information, and knowledge

3.1 Data, information, and knowledge

This category groups the data, knowledge management, and interoperability features with their respective functionalities.

3.1.1 Data

The data feature can be divided into three enabling functionalities: data structures, data processing (each with three maturity levels), and data integration (with five maturity levels) (see Fig. 1). Data structures develop in maturity as they progress from unstructured to fully structured models, and data processing matures as it transitions from raw data collection to data analysis that allows for real-time knowledge processing [64]. For data integration to reach a higher level of maturity, it has to go through the following process [65].

1. Integration is non-existing, data about manufacturing is not stored, and manufacturing equipment is not integrated with the IT systems.
2. Traditional information pyramid is implemented, machines are integrated and managed by a Manufacturing Execution System (MES).
3. Relevant manufacturing data is integrated with other data.
4. Implementation of Service-Orientated Architectures allows for data provisioning. To improve the efficiency of communication, an enterprise service bus connects data between enterprise and shop floor systems.
5. Real-time analytics extracts information from data, bringing the need for integration between all systems, devices, and data across the entire product life cycle; data insights are employed to optimize the factory and all manufacturing processes.

3.1.2 Knowledge management

Knowledge is the aggregation of information, which in turn is the processed aggregation of data, and the insights offer value to the manufacturing system. Knowledge management is the ability to store, manage, and deploy acquired knowledge effectively. Lowest levels of autonomy do not require knowledge management, but as the level increases, knowledge management becomes crucial, and it is achieved with knowledge design and historical data analysis. As it progresses to the most advanced maturity, it shifts from manual knowledge extraction and utilization to automatic identification and exploitation.

1. No knowledge management is utilized.
2. Low-level knowledge representation of assets and running processes that help identify the current system context.
3. Explicit knowledge design is required to be context-aware and self-adaptable to disturbances, though human operator feedback is still essential.
4. Knowledge management combines of manual knowledge design and analysis of historical data; the system self-improves with every iteration.
5. No manual knowledge design is required by humans. The system is able to analyze the raw data of its underlying processes to discover insights.

3.1.3 Interoperability

Communication between the system's components is a key enabler to achieving a high level of autonomy, interoperability is considered as one of its prerequisites. Information sharing is necessary between all business levels and therefore is not only limited to software or hardware infrastructure but to the process and information itself, supported by standards and validation methods.

At lower levels of maturity (see Fig. 1), interoperability is limited to compatibility at the infrastructure level. As the maturity level increases, standardization in production and business-related processes and information management is required, followed by protocols and methods to guarantee knowledge interoperability. At top levels of maturity, methods for certification and validation of interoperability would be required, combined with interoperability of non-technical high-level goals and business priorities [66, 67].

3.2 Process

Process refers to the manufacturing processes that create value in the system. This category encapsulates the features and functionalities of process synchronization, optimization, and reliability (see Fig. 2).

3.2.1 Synchronization

The synchronization aspect in production system autonomy is categorized into two types; material and logistical synchronization and physical synchronization [68]. The former is managing part and material movement to ensure stations are not left idle, and the latter is concerned with line-wide synchronization of processes, e.g., establishing a takt time. At the lowest maturity levels, no logistic synchronization between each station is employed, and parts and materials follow a manual philosophy. At level three, physical synchronization is realized: parts are produced at a synchronous rate at each cell and regularly transported to prevent unnecessary queuing or starvation. At level four, the system could maintain this behavior independently but still requires human assistance to start, stop, or change certain aspects of behavior. At level five, this becomes completely

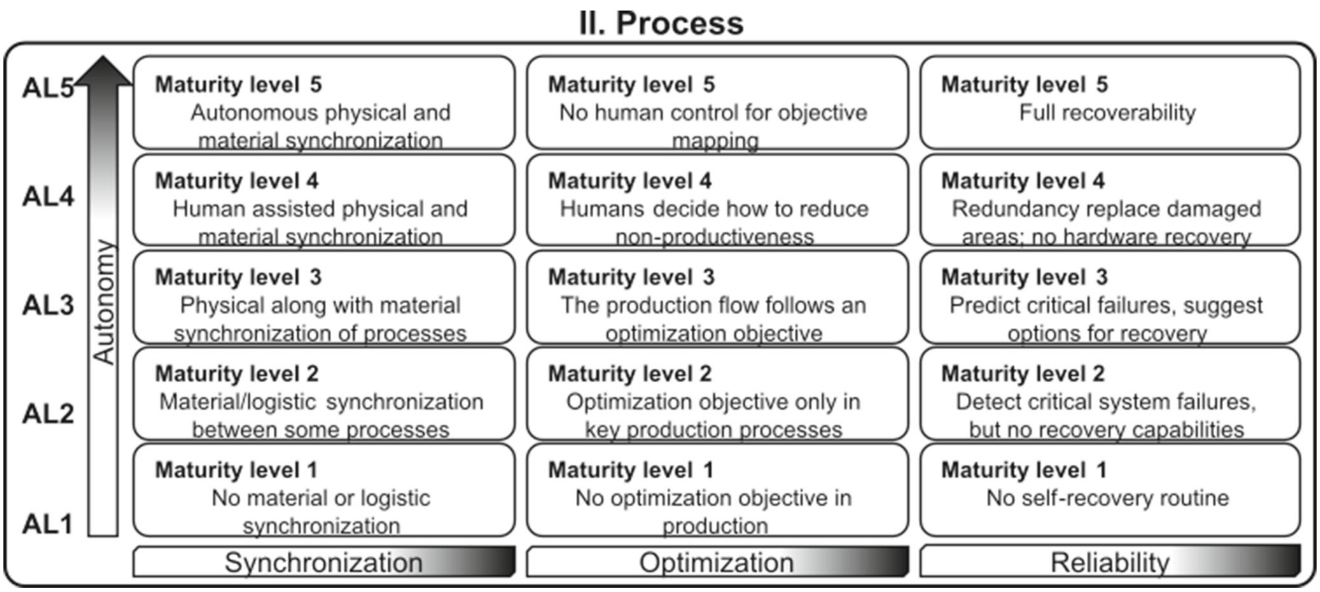

Fig. 2 Maturity levels of category II. Process

independent without human assistance: the system decides the rate and other conditions for synchronization.

3.2.2 Optimization

Optimization is identifying the productive and non-productive aspects of a system and maximizing the productivity, and minimizing the non-productive aspects in a manner akin to lean manufacturing. At the lower maturity levels, there are no capabilities in the production system for optimization. As the autonomy level increases, data collection of relevant data is implemented at individual processing stations. At higher levels, data for the whole production line is gathered, making it possible to assess and display the productive and non-productive components of the operation. Level four takes the collected data and links it to the objective: both the total productive and non-productive contributions are identified, but a human operator is required to decide on how to implement the optimization actions. At level five, no human control for optimization is necessary, and the system optimizes itself.

3.2.3 Reliability

The reliability of a system needs to be considered for its autonomy. The ability to overcome failures during operation is a critical feature that would ensure continuous and effective operation. A “failure” — as intended here — can include both a total breakdown, but also failure to produce parts at the required quality. At maturity level zero, a system cannot detect or respond to failures. As maturity increases, the system gains the ability to identify that an error has occurred and respond safely. Later, it will diagnose failures and gather the information that allows the system to predict them. Also, with growing maturity, it becomes less and less common to experience unpredictable variations in process quality, with less disruptions for parameters such as productivity and production cost. Going further, higher levels of maturity will have a recovery routine that will help the system to reallocate resources to avoid stops or disruption to its operation, and in case of lack of process stability, bringing a process back into control. This could be done at the software and hardware level (if backup systems are included), and it may involve informing human workers on what actions are required, or (at level five) executing the recovery plan itself.

3.3 Interactions

Though interoperability allows for data exchange, acting upon the data is required for interaction. Seamless interaction among humans, machines, and devices is a requirement of autonomous manufacturing systems that are able to control the interconnected manufacturing process flows (see Fig. 3).

3.3.1 Context-aware interactions

Context awareness is the ability of the system to interpret, adapt resources, and associate data with the system’s environment to better understand the situation the system is in and how data should be best used [69, 70].

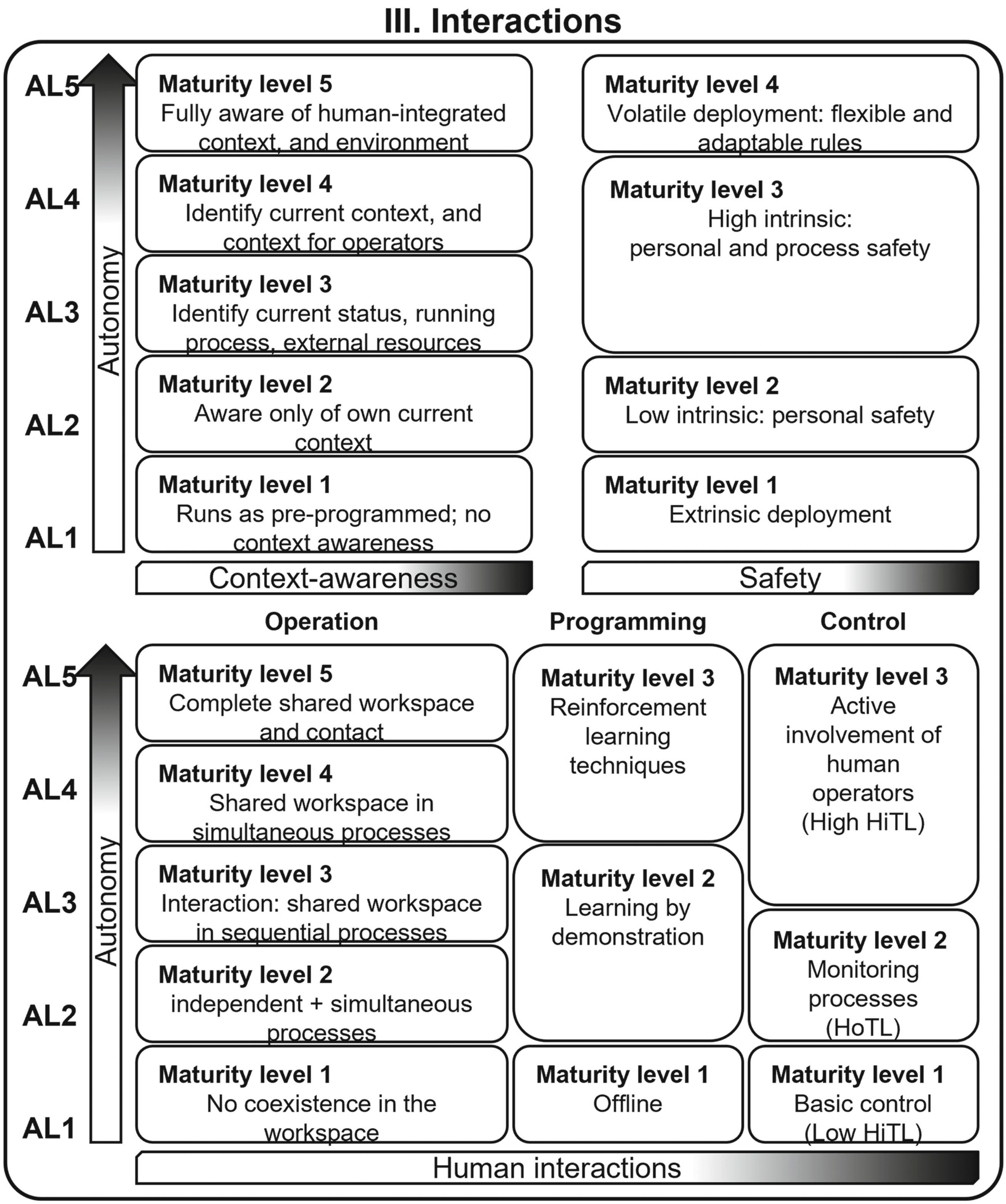

Fig. 3 Maturity levels of category III. Interactions

The increase in the level of autonomy will require an enhancement of context-awareness features. Non-autonomous systems run pre-defined programs without being aware of surrounding contextual information and integration. As maturity increases, systems become aware of their context and adapt their operations to the currently running processes and the operation of other external resources. At the highest maturity levels, the system can identify its current context, running processes, external resources, and the context in which the human operator interacts with a system and the context of the environment, thus enabling other autonomy processes to increase their usability and effectiveness by taking environmental context into account.

3.3.2 Interactions with humans

The future of human-machine collaborations should be to enable the workforce to handle complexity by complementing rather than replacing human capabilities and skills [71]. Effective autonomy requires consideration of three aspects; the operation of the system, the programming of individual pieces of equipment, and the control of the overall system. In each case, the system includes both manufacturing machines, but also human workers, and enabling productive and safe collaborative systems is the priority.

A low level of autonomy requires strict protective measures where humans and machines interact, as the system cannot adapt to interactions between the two. As maturity increases, coexistence is possible, but with limited contact and the processes being performed independently. A more interactive level allows both actors to share the workspace and communicate. A cooperative operation is developed when both actors have their own objectives and goals from a mutually beneficial perspective. The highest level of maturity allows a complete collaboration between actors: they have compatible objectives and goals, and the work fluently follows coordinated and synchronized operations.

How a human instructs a machine to perform a task is complex. At low levels of maturity, programming involves writing instructions and uploading them to the machine. Higher maturity in this area enables learning through demonstration, based on the repetition of movements performed by the human operator. It requires a high knowledge of the process, but the program is written directly by the system, so it requires less programming knowledge. The highest level of autonomy occurs when the system autonomously understand its capabilities, as well as the

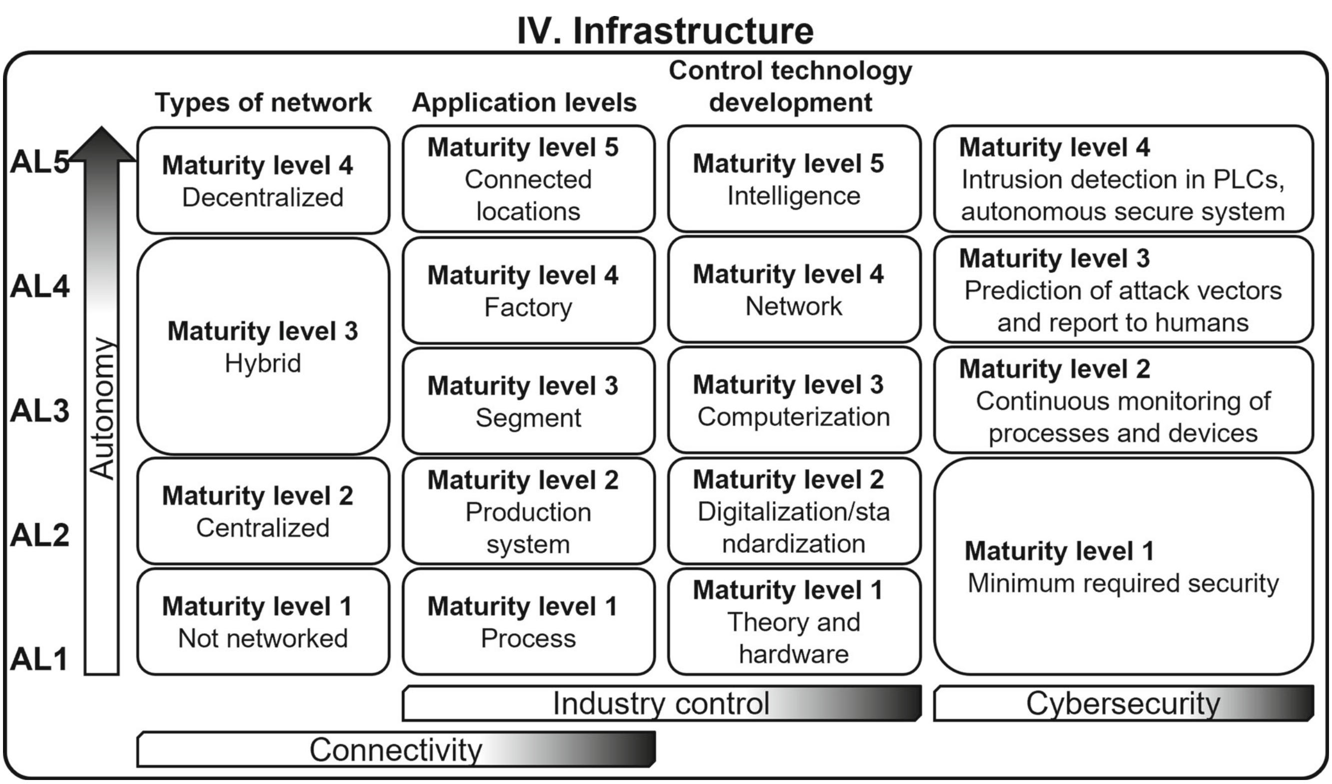

Fig. 4 Maturity levels of category IV. Infrastructure

tasks it has to perform without specific human guidance or as a collaborative partner in the process [72].

Manufacturing systems are combinations of humans and machines, and controlling the entire system effectively is challenging. Human-in-the-loop (HitL) control allows the integration of human operators, and communication between human and machines. As almost any system requires some minimal human intervention (system start/shutdown, continue command, etc.), a low level of mono-directional (i.e., human-to-the-system) interaction is required. At higher autonomy levels, the control role over the system can move to a more active one (high HitL), where the human operator is an integrated element of the system during main operations and task execution, with bi-directional information flow and awareness between the system and the operator.

3.3.3 Safety

Safety features in autonomous systems are classified as intrinsic or extrinsic. Low levels of safety maturity use extrinsic safety measures, which are external components such as light gates or floor scanners. At this level, the system is built rigidly, and uncertainty is reduced to the minimum. Medium maturity can use intrinsic safety measures based on built-in rules: systems consider safety measures before acting and require the participation of workers in rule management. A higher level of maturity will ensure process and personal safety. The highest maturity level includes flexible rules with high levels of adaptation to enable the system to respond safely to dynamic scenarios while at the same time being called upon to plan and reflect on their actions.

3.4 Infrastructure

Industry 4.0 helps the integration of various actors within the supply chain. However, this means the enabling a digital infrastructure is a factor that cannot be ignored [73] (see Fig. 4 for the maturity of features and functionalities).

3.4.1 Connectivity

Connectivity can be divided into two functionalities: the type and properties of the network being used and the levels at which the network is deployed. The type of network influences the available data exchange strategies while also determining how agile the system is to change. The application level is where elements of the production system are connected, from the low-level process and field elements to high-level connectivity between manufacturing sites. The efficiency of a system depends on how well the individual elements of the production system are networked, as this is a requirement for data exchange and collaboration in autonomous systems [74].

At the lowest maturity level, system elements are not networked and rely on the manual movement of data. At the maturity level, two networked elements receive information and feedback via a centralized server, so there is no direct communication between the elements. At maturity, four decentralized networked production elements can communicate with each other without a central unit, facilitating robustness to failure and simpler replacement of elements and systems.

3.4.2 Industry control

For the development of industrial control technology, two aspects are identified: control technology development and application levels. For control technology development, at maturity level 1, the theory and hardware are developed, while at maturity level 5, the intelligence technology for control theory should be developed. For application levels, at maturity level 1, the industry control is only applied in the process. As the application level goes up, the industry control can be used in bigger and more places. At maturity level 5, it will be expanded to connected locations.

3.4.3 Cybersecurity

Cybersecurity is the protection of information and operational technology infrastructure from internal and external threats. At maturity one, the minimum required security level is implemented (i.e., from government safety standards). At maturity level two, it is secured through the continuous monitoring of the running processes and connected devices. At maturity, three possible attack vectors can be predicted and reported to a human operator. The highest maturity level four has automatic intrusion detection either directly implemented into computers and controllers or with separate hardware. Either approach allows the system can secure itself from most attacks [75].

3.5 Self-X

As discussed in the background review, self-X properties are a collection of methodologies that enable systems to manage and control themselves. Self-X capabilities are required to reach higher levels of autonomy in future production systems, and the autonomous nature based on the self-X capabilities is needed to adapt to unforeseen environmental conditions and requirements. Figure 5 shows the full scale of capabilities that can lift it to another level of autonomy through the five levels of maturity we described.

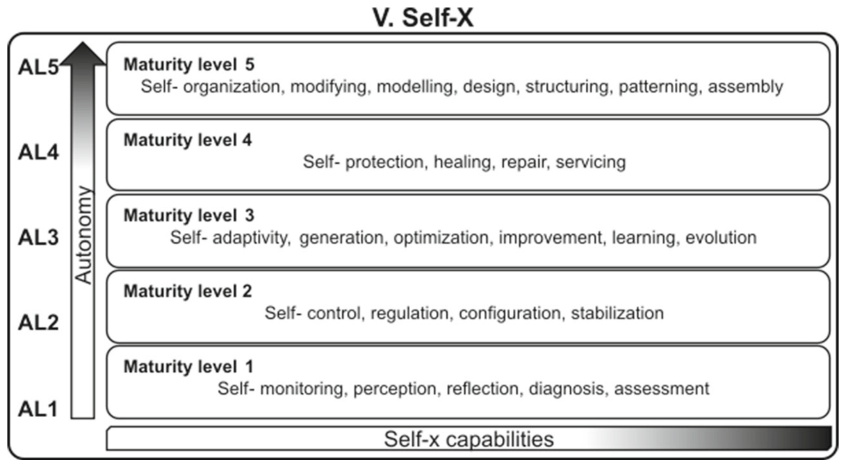

Fig. 5 Maturity levels of category V. Self-X capabilities

On lower levels, a system is able to monitor the environment and the process and assess if a fault is happening; it goes to the highest level of maturity where the system is capable of organizing processes, designing features, and structuring itself to intercept external attacks, repair faults, and damages, and adapt the production schedule to the demands placed upon it.

3.6 Measurement

Measurement of properties in a manufacturing process is essential to maintaining product quality. Measuring the performance of manufacturing processes is also critical for any system to understand how well the system is operating and what can be done to improve it. The suitability of measurement is a function of its accuracy, stability, and certainty [76] (see Fig. 6).

3.6.1 Accuracy

Accuracy encompasses all the qualities that a measurement device must have to be acceptably used in a defined task. "Precision" is considered the distance between the measured value and the "true" reference value of a measurement. The concept of accuracy also includes "repeatability"; the capability to replicate the same measured value for each reference value. The third functionality is "sensitivity," the ratio between a change in measurement value and a change in reference value. Sensitivity also includes the ability to distinguish true positives and true negatives from false positives and false negatives [77].

When measuring a manufacturing process's performance, the lowest levels of maturity have no accuracy determination mechanism, but this improves as the maturity level increases. At lower maturity levels, the calibration and setting of parameters require human intervention as the environment changes, but at the highest levels, the system continuously adapts the measurement processes to maintain accuracy despite changing conditions. At higher levels, an automatic increase of sensitivity is also possible without human intervention.

3.6.2 Stability

Over time, a measurement device could exhibit variations in the quality and reliability of the output value. If a device adapts to that and maintains standards of quality measurement, then it could be considered stable.

Low stability maturity offers no safeguards on the reliability of measurements. At medium levels of maturity, guarantees are made only if the environmental conditions remain constant. At high levels, systems can evaluate their performances based on historical data of operations and adapt to changing conditions.

3.6.3 Certainty

Whenever maintenance is needed for an instrument that measures properties, a calibration of this instrument is usually needed to verify its accuracy. This allows the operator to be certain of the measurement's reliability. Certainty takes into account the ability of a production system to validate measurements that are given as an operation input.

At maturity level one, the system measures values for a given operation cycle. As the maturity level increases, the system might be able to receive measurements for each operation in the cycle, but still without complete certainty. At a higher level, it takes into account the noise and identifies the factors that cause it. At the highest possible level, the system is capable of dealing with that noise factor by itself: it eliminates the errors to conduct the most precise operation it can. At this stage, no human effort is involved to clean the signal.

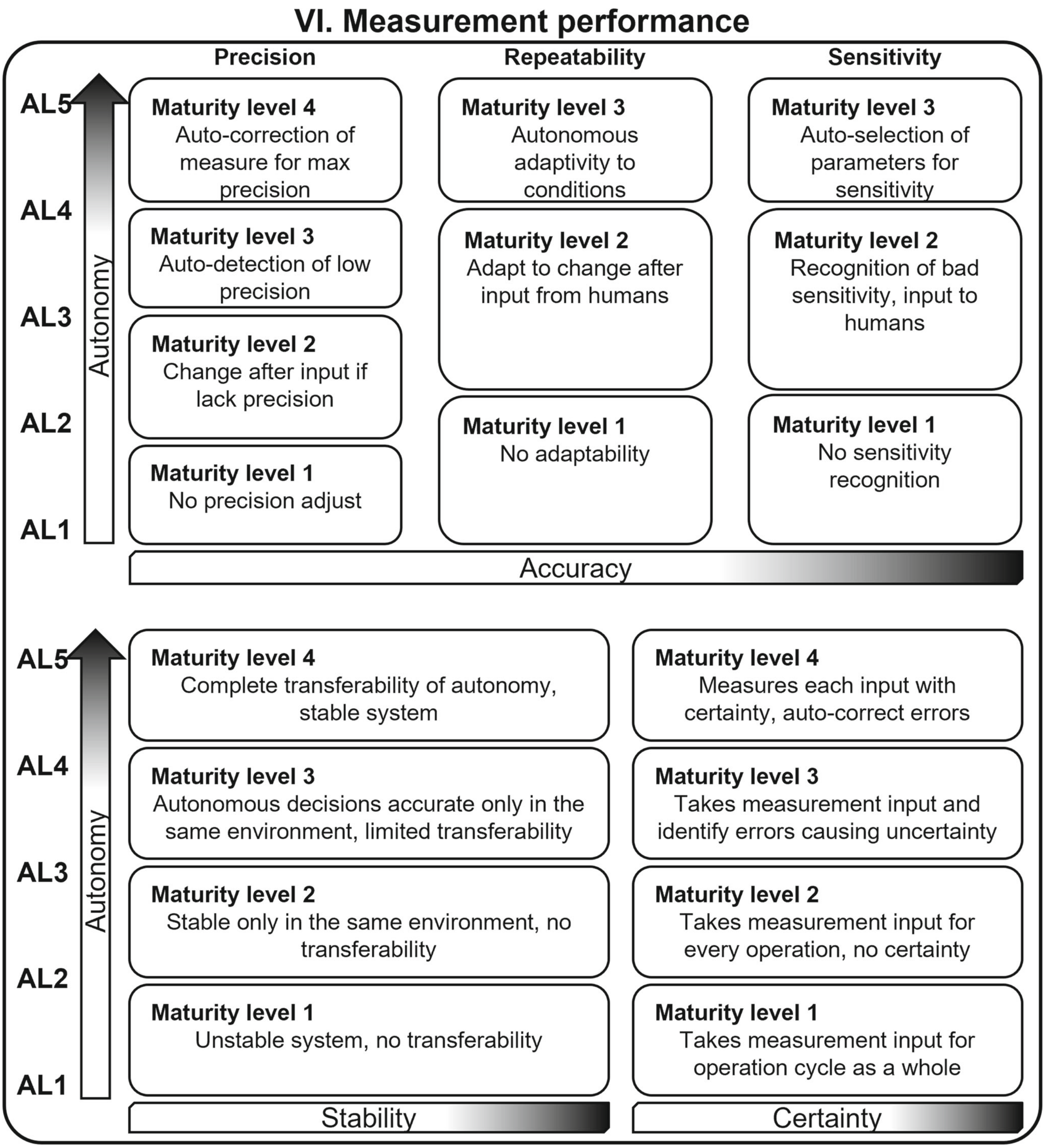

Fig. 6 Maturity levels of category VI. Measurement performance

4 Application and validation of the model

In this section, the IDEAS (Instantly Deployable Evolvable Assembly Systems) system is introduced to illustrate how to apply the model of autonomous features to a real system. It was an EU FP7-funded project that started in 2010 and ended in 2013. Its target was to develop evolvable assembly systems for two industrial customers, IVECO S.p.A. and Electrolux AB [78].

The main goal of IDEAS was to implement proxy technology in a commercially available control board, to enable distributed control at the workshop level. What is

Fig. 7 The ECU Assembly System (MASMEC) [78]

considered here is not the planning or logistics level, but the operational level of the assembly system.

Two industrial cells were built to verify the chosen approach. They were built at KTH (manufacturing) and MASMEC S.p.A. [79]. The products to assemble were an ECU (Electronic Control Unit) from a commercial vehicle and some specific washing-machine components. The MASMEC system was therefore designed to assemble two variants of the ECU, whereas the KTH system assembled three variants of the "feet" assemblies. Figures 7 and 8 illustrate the two production cells.

To demonstrate the use of the model, the ECU Assembly System (MASMEC) will be examined in detail.

The evaluation must be made on the separate categories of the workshop; therefore, if some of the components achieve autonomous behavior and others do not, based on the information from Section 3, the user must perform an overall evaluation and give an "averaged" score. If they want to go into more details, it is possible to clusterize sub-systems and perform the same evaluation on them as they would on the whole system. Then, they would obtain a value for each sub-system, and decide if they want to keep them separate, or merge them in an overall evaluation.

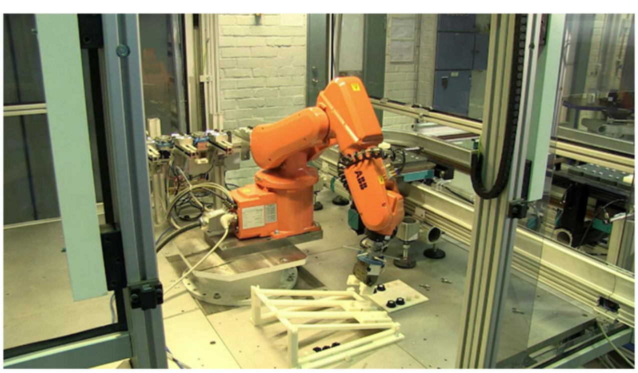

Fig. 8 The Washing Machine Components Assembly System (KTH) [78]

4.1 Data, information, and knowledge

The data feature can be divided into three functionalities: data structure, data processing, and data integration. This system utilizes verified data exchange protocols based on semi-structured data; therefore, the "data structure" maturity level score is ML2 [ML2]. The system is programmed to perform a real-time adaptation of the production based on the analysis of data streams that it receives, so it scores the highest maturity level for "data-processing" [ML5]. For "data integration," this system implements life cycle analysis, including goal and scope definition, inventory analysis, life cycle impact assessment, and life cycle improvement. There is an integration of cross-life-cycle data, but this system does not use digital twins [ML3]. Combining the above maturity levels of data features, the averaged autonomy level in the "data" feature is ML3.

The system uses data analysis as a key part of its functionality, but it is not able to self-analyze the raw data of the underlying processes, and it requires humans to implement knowledge design and the collected historical data. It, however, possesses a low-level knowledge of entities and running processes to help identify the context [ML2].

Principles of interoperability, multi-agent system programming, and OPC connection are used in this system, enabling efficient data sharing. But no knowledge and information interoperability principles are utilized in this system [ML3].

Combining the above maturity levels of data feature, knowledge management feature, and interoperability feature, the autonomy level of the category of data, information, and knowledge is AL3 (I-AL3).

4.2 Process

The category process has three features: synchronization, optimization, and reliability. The ECU Assembly systems have material synchronization in their manufacturing operations. It also features a partially automatic unloading station, (see Fig. 7) [ML3]. For optimization, no identification of productive and non-productive work in the system is performed [ML1]. Reliability: This ECU Assembly system has no self-recovery routine [ML1]. Considering the mentioned features, the autonomy level of the process is (II-AL2).

4.3 Interactions

Seamless interaction between humans, machines, and smart devices has three features in our autonomous model: context-aware interactions, interaction with humans (in terms of operation, programming, and control), and safety. The system runs as pre-programmed without being aware of the current context [ML1]. As mentioned in Section 3, the interaction with humans has three functionalities: operation, programming, and control. Humans are required to unload the workpieces manually, but other processes are automated in the ECU Assembly system [ML2]. No learning by demonstration and reinforcement learning are used [ML1]. The assembly system does not integrate the human operator and monitoring process [ML1]. To summarize, the maturity level of interaction with humans can be assigned as ML2. The only safety measures deployed during this project are extrinsic and external components, so there is no autonomy involved in safety deployment [ML1]. In conclusion, the autonomy level of interaction is (III-AL1).

4.4 Infrastructure

As mentioned in Section 3, the category of infrastructure has three features: connectivity, industry control, and cybersecurity. The ECU system is a fully connected production system [ML2]. The types of networks are still unclear. This system uses an agent-based control architecture that considers manufacturing components as mechatronic agents that can be plugged or unplugged to create systems, without reprogramming [80]. The control technology is applied to the production system level and is applied in a network with the other components of the system [ML3]. A key challenge for this cell is in creating an architecture for which an effective control structure can be instantiated for any assembly system layout. As the demands on assembly are extremely diverse (see [78]), this poses some challenges. The final Mechatronic Architecture is based on four basic agents: (1) Machine Resource Agent (MRA); Coalition Leader Agent (CLA); Transportation System Agent (TSA); Human Machine Interface Agent (HMI-A). This system cannot predict possible attack vectors and the IT infrastructure is also not secure through the running processes and connected devices [ML1]. This category has better scores than the previous category, and its overall score is (IV-AL2).

4.5 Self-X

Category self-X consists of four features: self-configuration, self-healing, self-optimization, and self-protection. The IDEAS project developed reconfigurability and holonic manufacturing principles. This system included the first self-reconfiguring system demonstration and new mechatronic architecture, and its main strength was its self-configured modules [78] [ML4]. However, this system was limited in self-healing, self-optimization, and self-protection [ML1]. In conclusion, the assigned autonomy level for self-X is (V-AL2).

4.6 Measurement

Measurement performance is split into three features: accuracy (precision, repeatability, and sensitivity), stability, and certainty. This system was able to compensate for low precision in measurement (though it depends on input from external sources) [ML2]. The control boards functioned very well in more than two different applications. The manufacturing system was thoroughly tested to be perfectly functioning at other partners' labs [81]. They adapted to change and worked under new conditions, after input from humans [ML2]. Low sensitivity in measurements was detected and human operators were signaled [ML2]. The maturity level of the "accuracy" feature is ML2. The decision-making process implemented on the board during production processes was stable [ML3]. The system made measurements for every operation performed to enable adaptation of the production process when needed, but it was unable to identify errors that may cause uncertainties [ML2]. Overall, the autonomy level for measurement performance is (VI-AL3).

4.7 Summary table

We summarized the results of the evaluation in Table 3, showing the maturity levels of the features (averaged for those features that have multiple functionalities), and the Autonomy Levels assigned to each category by exploiting the description and figures in Section 3.

The Autonomy Levels are in the range between 1 and 3 (out of a maximum of 5), meaning that this system did not reach the highest levels of autonomy. This system did not complete the transition from Autonomous Level 2 (AL2) to Autonomous Level 3 (AL3), as defined in Section 3, so it is not an Adaptable Factory. However, this was expected both because it was developed before the popularisation of the Industry 4.0 concept, and because this model is intended to encompass technology developments in short to medium term — current approaches do not implement all the required features simultaneously to get to the maximum level of autonomy described in this paper. The reader can visualize a summary of the scores in Fig. 9.

The final goal of the model is to provide maturity characterization of the features of a system, so that the user can easily visualize where they would need to act to increase the overall level of maturity. Giving a numerical

Table 3 Summary of autonomy and maturity scores for ECU Assembly System application for the validation of the model

Category	Autonomy level for categories	Feature	Maturity level for features
I. Data, information, and knowledge	I-AL3	Data	3
		Knowledge management	2
		Interoperability	3
II. Process	II-AL2	Synchronization	3
		Optimization	1
		Reliability	1
III. Interactions	III-AL1	Context awareness	1
		Interaction with humans	2
		Safety	1
IV. Infrastructure	IV-AL2	Connectivity	2
		Industry control	3
		Cybersecurity	1
V. Self-X	V-AL2	Self-configuration	4
		Self-healing	1
		Self-optimization	1
		Self-protection	1
VI. Measurement performances	VI-AL3	Accuracy	2
		Stability	3
		Certainty	2

overall level of maturity would rely on the personal interpretation of the lead evaluator; averaging the scores in the categories provides little additional information, since they are separate and refer to different aspects. By doing so, the user can concentrate on the individual values and address them separately.

As many CMMIs experienced in the past, the issue of flawlessly evaluating the system is of utmost importance. Any assessment process comes with inaccurate, missing, and misunderstood information. Moreover, it often happens that certain levels of the model overlap, causing confusion and leading to subjective judgement of the evaluation. Researchers tried to fix this problem by applying scoring systems that rely less and less on the subjective judgement of the evaluator, based on fuzzy quantitative benchmarks model [82], and Fuzzy Expert System [83], which is a simple but effective approach to solve fuzzy aspects such as overlapping between maturity levels. We state that our model does not yet conforms to such systems, but it will be our next priority to set the validation of the ECU example to said more trustworthy evaluation systems.

4.8 Limitations

One of the main limitations of the model is that the authors assigned the highest maturity levels for features where the technology is currently not employed in manufacturing. Therefore, the highest maturity levels are still impossible to reach outside some research demonstrators. The system evaluated here focused on running with a multi-agent control setup, being able to re-configure on the fly, and having self-configuring modules. For these aspects, it performs excellently, but it was not intended and developed to meet all the criteria needed to reach full autonomy [84]. It had a specific purpose, and it achieved it with prowess. This model is a guide to autonomy and how it could be implemented, but we acknowledge that high levels of autonomy are not the goal for most manufacturing systems, though we believe that it brings a high added-value where autonomy is required. Another limitation is that in some fields of manufacturing not all the categories of features of the model are present or easy to evaluate. A solution would be to exclude those features from the evaluation and complete the evaluation without them. However, this would limit the possibility of comparing it with other product solutions.

Since the criteria for evaluation of features of the model are sometimes qualitative, discrepancies might appear between evaluations made by different people on systems that may seem similar. However, the description of the features that we provide is clear and supported by established literature on the topic, so analysts that perform the

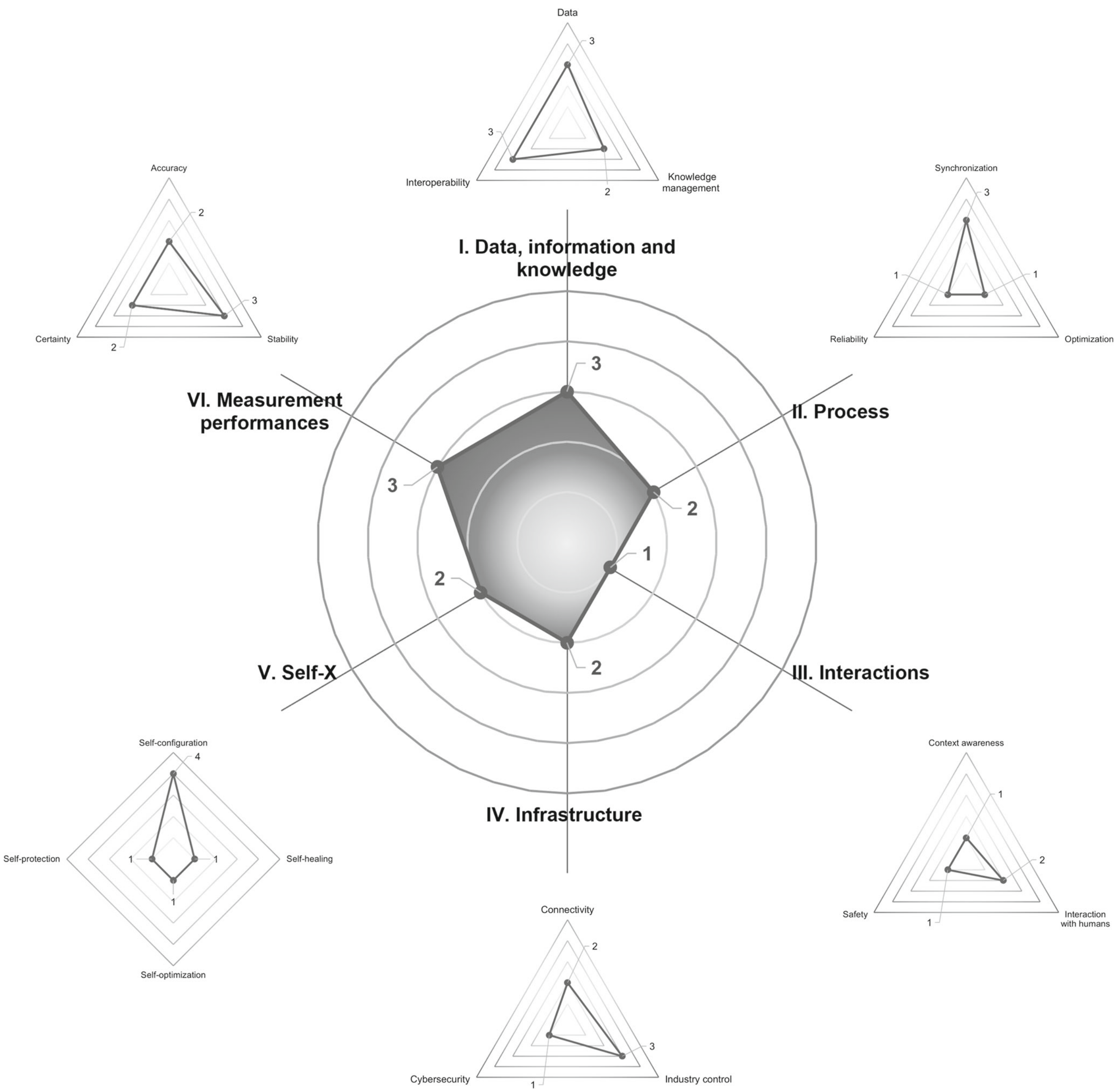

Fig. 9 Complete representation of the model scores for ECU Assembly System: Autonomy Level is on the axis of the diagram in the center, maturity scores for the features in the diagrams around it

evaluation might refer to the provided literature whenever in doubt.

Numerical judgement of the features based on some experimental testing setup and data extraction would be optimal, but it would require additional time and a big amount of resources to be performed, and especially would require to be performed on a selection of systems, and not a single one. Therefore, we relied on this example for the work in this manuscript, and we defer to future research for additional data examples.

5 Conclusion

Industry 4.0 brought digital systems to the forefront of manufacturing development, leading to major transformations in manufacturing requirements, capabilities, and operational systems. Autonomy is a key goal achievable through digitalization, and this paper presents an investigation of the definition of autonomy in both the scientific and industrial communities. The main contributions of this paper are threefold: first, a background work analysis helps clarify autonomy goals and definitions in manufacturing systems. Secondly, the analysis provides a list of the required features of autonomous systems that support the implementation of autonomy in manufacturing. Thirdly, a five-stage model is designed to guide the evaluation of a particular manufacturing system and pave the way for the gradual transition towards autonomy.

Section 2 starts with the definition of autonomy with its goals in the manufacturing context. The difference between autonomy and automation is also in the key ability of an autonomous entity to face unanticipated situations and adapt its course of action as they appear. Furthermore, a variety of engineering domains in which autonomy applications were reported in the literature is also provided, ranging from unmanned vehicles to manufacturing areas.

This leads to the five-level model of autonomy in manufacturing systems, from no autonomy to a fully autonomous factory. Low autonomy level manufacturing systems can be highly effective in pre-defined situations but will depend on human decisions to react to unanticipated contexts. Conversely, the highest level implies total independent cognitive functioning mechanisms on different features in terms of data, information, and knowledge, process, interaction, infrastructure, self-characteristics, and measurement performance.

The system view of these levels is broken down into the contributing features as indicated by Table 2, and Section 3 shows the different features associated with maturity levels. As the maturity level of these features and functionalities increases, the overall autonomous level of the manufacturing system also increases. This approach allows the identification of factors that may be holding a system back from achieving its autonomous potential. The validation of the model performed in Section 4 confirmed that the model could be used to evaluate autonomous systems.

Even though the effort toward autonomy implementation is growing, in current leading manufacturing industries — such as semiconductor, aerospace, and automotive — the highest autonomy level has not been achieved. Development of this work in the future will provide an investigation of the barriers and challenges that hinder the development of autonomous features in the industry, as well as an analysis of the business models and considerations that may hold back an otherwise technically possible implementation.

Using the model presented in this paper to evaluate other manufacturing systems that aim to reach smart manufacturing and complete autonomy would provide a benchmark for other companies that are interested in investing in this evolution program, as well as evaluating at two-point times one system that is currently experiencing a transition from lacking autonomy in its manufacturing plant to a completely autonomous system. The authors are putting their effort into finding such systems to evaluate, and an opportunity might be provided by the FA3D2 experimental test-bed [85], which will be a technology demonstrator for the authors involved in the paper.

Appendix

The authors would like to append to the manuscript the summary Fig. 10 to give the reader a complete overview and the checklist of all the features to be graded in the model, along with Fig. 11 in the Appendix, where the score can be inputted and visualized (as in the example in Section 4, see Fig. 9).

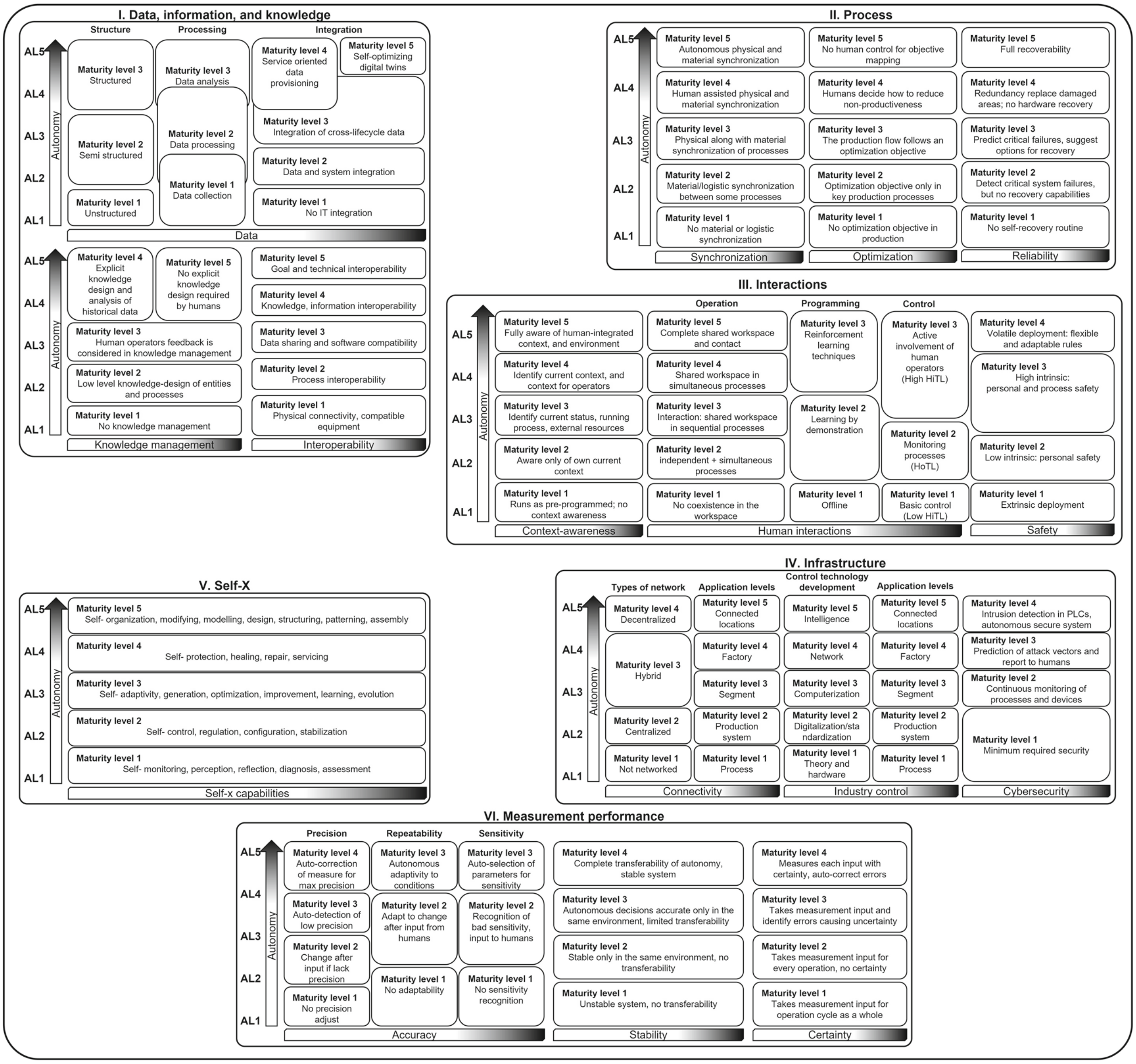

Fig. 10 Checklist and summary of the complete model

Author contribution Fan Mo: conceptualization, methodology, writing — original draft. Fabio Marco Monetti: conceptualization, methodology, writing — original draft. Agajan Torayev: conceptualization, methodology, writing — original draft. Hamood Ur Rehman: conceptualization, methodology, writing — original draft. Jose A. Mulet Alberola: conceptualization, methodology, writing — original draft. Nathaly Rea Minango: conceptualization, methodology, writing — original draft. Hien Ngoc Nguyen: conceptualization, methodology, writing — original draft. Antonio Maffei: supervision. Jack C. Chaplin: supervision, writing — review and editing, funding acquisition.

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Data Availability If needed, we could provide.

Code availability No

Declarations

Ethics approval Yes

Consent to participate Yes

Consent for publication Yes

Conflict of interest The authors declare no competing interests.

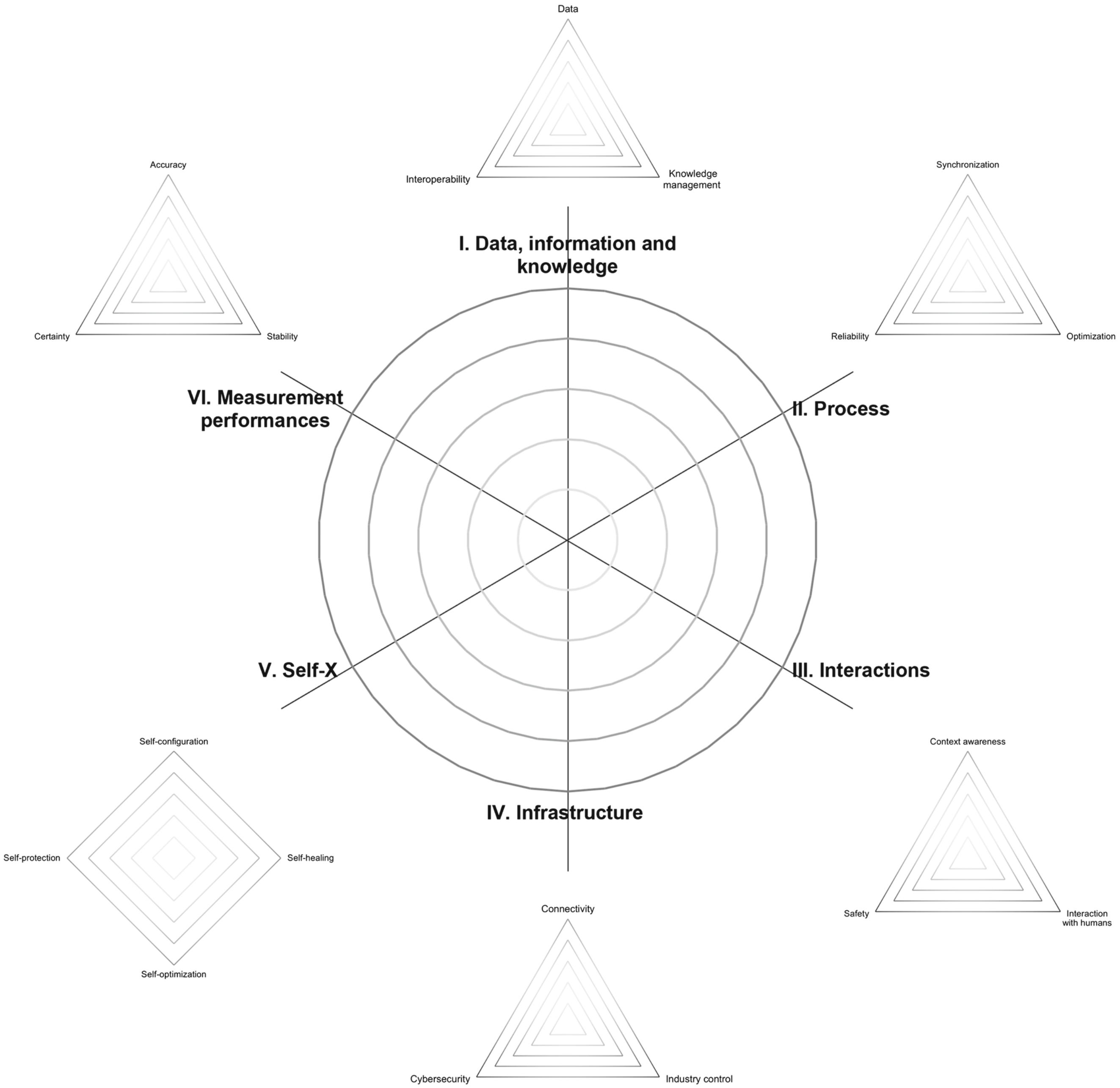

Fig. 11 Representation of the model — empty

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