AI Platform for Integrated Sustainable and Circular Manufacturing

Deliverable

D3.1 Conceptual Framework and Reference Architecture - 1st version

Actual submission date: 31/03/2023

Funded by the European Union

Project Number:	101058585		
Project Acronym:	Circular TwAIn		
Project Title:	AI Platform for Integrated Sustainable and Circular Manufacturing		
Start date:	July 1st, 2022	**Duration:**	36 months
D3.1 Conceptual Framework and Reference Architecture - 1st version			
Work Package:	WP3		
Lead partner:	ENG		
Author(s):	Gabriele De Luca, Elisa Rossi (ENG), Claudio Capuzzimati, Rosario Pirrotta, Vincenzo Cutrona (SUPSI)		
Reviewers:	John Soldatos (INTRA), Sergio Gusmeroli (POLIMI)		
Due date:	31/03/2023		
Deliverable Type:	R	**Dissemination Level:**	PUBLIC
Version number:	1.0		

Revision History

Version	Date	Author	Description
0.1	31/01/2023	ENG	First ToC
0.2	9/03/2023	ENG	Contribution to section 4 and 5
0.21	10/03/2023	POLIMI, FhG-IOSB, INTRA, GFT	Contribution on relevant projects section 4.2
0.22	17/03/2023	SUPSI	Contribution to section 2 and 3
0.3	17/03/2023	ENG, SUPSI	First integrated version
0.31	22/03/2023	ENG, SUPSI	Revised content with INTRA and POLIMI feedback
1.0	31/03/2023	ENG	Final coordinator review before submission

Table of Contents

List of Figures

List of Tables

Definitions and acronyms

AAS	*Asset Administration Shell*
AI	*Artificial Intelligence*
ALTAI	*Assessment List for Trustworthy Artificial Intelligence*
AM	*Additive Manufacturing*
API	*Application Programming Interface*
AR	*Augmented Reality*
BDV	*Big Data Value*
BDVA	*Big Data Value Association*
BM	*Business Model*
BSI	*British Standard Institute*
CA	*Consortium Agreement*
CBM	*Circular Business Model*
CE	*Circular Economy*
CI	*Collaborative Intelligence*
CPFI	*Circular-process feedstock intensity*
CPU	*Central Processing Unit*
CR	*Collection Rate*
CRUD	*Create Update Delete*
DaR	*Data at Rest*
DFR	*Design For Recycling*
DLT	*Distributed Ledger Technologies*
DiM	*Data in Motion*
DL	*Deep Learning*
DSS	*Decision Support System*
DT	*Digital Twin*
EC	*European Commission*
ERP	*Enterprise Resource Planning*
EU	*European Union*
GA	*Grant Agreement*
GDPR	*General Data Protection Regulation*
GPU	*Graphic Processing Unit*
GUI	*Graphical User Interface*
IEML	*Ethical AI & Machine Learning*
IoT	*Internet of Things*
ISO	*International Organization for Standardization*
IT	*Information Technology*
KPI	*Key Performance Indicator*
LCA	*Life Cycle Assessment*
ML	*Machine Learning*
PLE	*Product Life Extension*
PLM	*Product Lifecycle Management*
RA	*Reference Architecture*
RAM	*Random Access Memory*
RPO	*Retain Product Ownership*
SSO	*Single Sign On*
TF	*Task Force*
UK	*United Kingdom*
WEEE	*Waste Electrical and Electronic Equipment*
WP	*Work Package*
XAI	*eXplainable Artificial Intelligence*

Disclaimer

Executive Summary

Circular TwAIn researches, develops, validates, and exploits a novel AI platform for circular manufacturing value chains, which will support the development of interoperable circular twins. The Project is destined to develop sophisticated digital twins for circular manufacturing, which will be comprised by many different novel technologies that will be effectively integrated to support end-to-end sustainability across the circular manufacturing chain. One of the main success factors of such challenging Project there is the set up a solid technical baseline that can be considered as a reference from both technical and end users partners. This document aims at positioning as such baseline reporting on the Circular TwAIn reference architecture and all the preparatory activities required for its definition.

The document provides the technical background for understanding how to design and develop AI-based digital twins for resilient and circular manufacturing in value chains in the scope of the Circular TwAIn Project.

Section 2 investigates the development and methods in value chains management in the context of circular economy (CE) with aim of setting solid foundation on which Circular TwAIn would rely. Specifically, it is intended to provide models and alternatives to keep products in use, whenever possible, when they reach the end of their lives. This section also highlights recent advances in the area of circular indicators to measure the performance of circular strategies.

Section 3 highlights the potential of AI and CI to significantly promote the circular economy and discuss the importance of investment in research and development in these areas to speed up progress towards a more sustainable future. Despite the numerous and obvious benefits of AI and CI, Section 3 reports some concerns regarding their potential negative impacts, especially concerning trustworthiness. Trustworthy AI refers to AI that can function in a dependable, transparent, and ethical manner while also safeguarding fundamental human values and rights. Similarly, trustworthy CI necessitates ensuring that the collective intelligence of human and machine participants is developed and utilized in a way that is equitable, transparent, and benefits all involved stakeholders.

Then, this first version architecture (M9) is the outcome of a three-step design methodology which started with relevant technology exploration, and has been followed up through a closer examination of the most prominent reference architectural models provisioned for Manufacturing and Circular scenarios (mainly reported in Section 4). A top-down design approach was then carried out using the original Circular TwAIn architecture proposition as a starting point to identify the various components and subsystems that deliver on the specified needs and requirements of the end-users (Section 5). Through this exercise, the architecture was broken down into a Cloud Layer (Collaborative and Explainable AI, and Human and Applications), an Edge Layer, an Observable Layer (for external data sources) and Horizontal and Vertical to represent also Data Spaces specifications on relevant domains and other relevant data features. Each one of these base elements is presented from a functional standpoint, while for a deep definition of the technologies and development other deliverables of technical WPs (WP4 and WP5) will be the reference.

The functional view presented in Section 5, delivers a high-level overview of the envisioned system functionality broken down into the identified subsystems and individual components,

all of whom are described in terms of their foreseen roles and responsibilities within the runtime operation of the system. Aspects related to integration, such as the interrelationships among platform components are presented, in order to guide the development of the necessary intercommunication mechanisms between components. This process is critical to guarantee the proposed Reference Architecture is fully aligned with the Industry 4.0 reference architecture models and principles that have been considered as relevant for the Project.

The contents of this deliverable are the results achieved by Task 3.1 - Resilient and Circular Manufacturing in Value Chains, Task 3.2 – Trustworthy AI and Collaborative Intelligence, and Task 3.3 - Reference Architecture and Distributed Intelligence between M3 and M9, and provide a first version documentation of the envisioned system's shape and structure, and are expected to be updated upon completion of the architecture and system specification activities at M27.

1 Introduction

1.1 Scope of the document

The current deliverable represents the Circular TwAIn's Consortium preliminary attempt at defining a modular, service-oriented architecture for the Circular TwAIn proposed solutions. The document aims to serve as a reference guide for the Consortium partners who are engaged in the technical implementation of the Project, and are responsible for the development of the components that will comprise the architecture.

The components, information flows and topological considerations described in this deliverable are the result of a combination of activities undertaken in the context of Task 3.3 "Reference Architecture and Distributed Intelligence" during the first 9 months of the Project lifetime. These activities supersede the results of the initial architecture definition (that took place during the Project proposal preparation stage), and encapsulate, among exploratory and design activities also the results of joint discussion with other technical WPs and the expectations of the end-users (demonstrators). The report in particular comprises all the background technologies that have been identified and proposed by Project partners during the preparation of the proposal and during the first months of Circular TwAIn. As well, some projects/initiatives of interest for Circular TwAIn are presented and discussed.

A comprehensive view of the relationship between the technical components depicted in the reference architecture and the requirements that have been carried out from the activities of WP2 and WP6 is provided to legitimate technical resolution agreed by the Consortium members.

Since requirements, as well as parts of the architecture are subject to change in the remainder of the Task (M10-M27), this deliverable should be treated as an initial reference, that describes the foreseen building blocks, their relationships and their rationale over existing literature. As a result of these ongoing activities, an updated version of this deliverable ("Conceptual Framework and Reference Architecture – 2nd version" – D3.4) will be submitted in the second half of the Project (M27).

1.2 Document Structure

Apart from the Introduction and the Conclusion and Future Outlook sections that present the rationale and the results of the activities carried on by the first three tasks of WP3 (T3.1, T3.2 and T3.3), the rest of the document is structured as follows:

- Section 2 explains the methodology that will be followed to address the activities of the task. It also provides a state-of-the-art analysis of business models and indicators in the context of the circular economy.
- Section 3 discusses the main principles for implementing trustworthy AI, reports some potential applications for CE and proposes some frameworks and toolkits to support the assessment and improvement of AI solutions towards trustworthiness.
- Section 4 provides a full review of the state-of-the-art technologies, frameworks and initiatives that have been selected as of interest for Circular TwAIn.
- Section 5 describes the first Reference Architecture that has been elaborated: special care has been directed on (i) the presentation of different views to better

highlight the multiple technological aspects playing in Circular TwAIn (AI and DT), (ii) on the adherence with the principles and references reported in Section 4 and (iii) on mapping the high level requirements that have been identified so far by the three pilots of the Project.

2 Approaches to Resilient and Circular Manufacturing in Value Chains

2.1 Methodology

To provide solid foundations on which Circular TwAIn would rely, T3.1 will research current developments and methods for resilient and circular manufacturing in value chains. Without ignoring cross-sectoral aspects, this analysis will focus primarily on the industries that are involved in the Project's pilots. If anything, these will be given extra consideration because a variety of opportunities may arise from industries and domains that are not closely related in traditional business. Figure 2-1 represents the flow of activities planned to achieve the objectives of the task, broken down by the version in which they will be addressed.

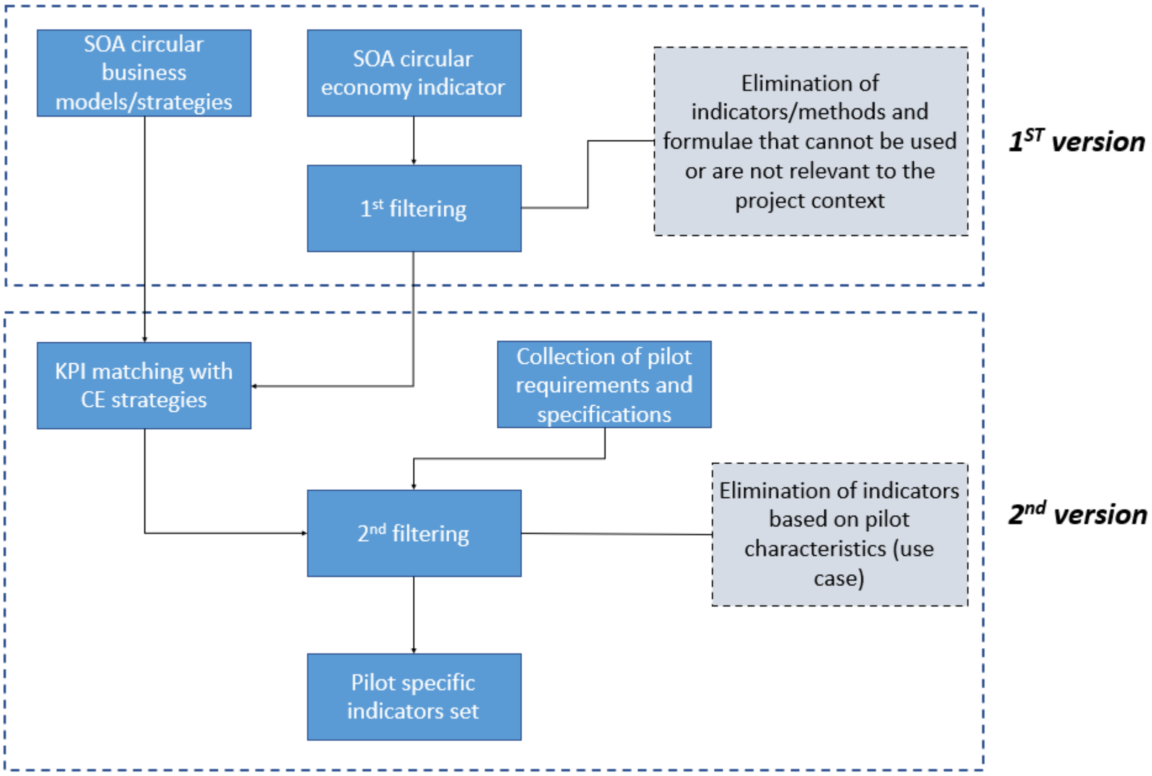

Figure 2-1: T3.1 planned workflow

The first version of this deliverable contains the literature study of circular business models and indicators. Specifically, the objective of the first phase is the analysis of strategies and practices that support the transition from a linear to a circular economy, as well as the identification of metrics to determine their performance. The first stage of indicator development is based on the results of the EU TREASURE Project 72[1] to which a set of filtering logics were applied, which are illustrated in Section 2.3. In the second version of the document, the resulting set of indicators will be matched with the previously identified circular economy strategies. In this context, the activity of collecting pilot specifications and requirements will be fundamental for the second filtering phase with the objective of eliminating all remaining indicators not suitable with the identified use cases. Finally, the resulting indicators will be assigned to the various pilots with the objective of assessing circularity performance.

2.2 State-of-the-art of circular economy strategies

The world needs a more sustainable economy, which necessitates activities that adhere to the three principles of maintaining products within the value chains. The circular economy is a critical response to this requirement (Ying, 2012) [3]. According to Frishammar and Parida (2019, p. 8) [2], a circular business model is one where a focal company, in collaboration with partners, uses innovation to create, capture, and deliver value to improve resource efficiency by extending the lifespan of products and parts, thereby realizing environmental, social, and economic benefits. The basic logic of circular business models (CBMs) is built on using the economic value that remains in items after usage to create value (Evans et al., 2017 [3]; Linder & Williander, 2017 [4]). In order to give an overview of different classification frameworks a list of the most commonly [5] used approaches has been shown below.

ReSOLVE framework (Ellen McArthur Foundation)[1]

The Ellen MacArthur Foundation states that Circular Economy (EC) is founded on three principles, all of which are design-led: (a) making sure that products are used more frequently and for longer periods of time, (b) that they are made of materials that have a lower environmental impact, such as recycled materials or resources derived from renewable sources, and (c) that they are designed to be reused once they have reached the end of their useful lives. When the principles of the circular economy are put into practice, consumers receive better goods and services (for example, because they are more durable), a more reliable supply chain (because the emphasis on life extension and reuse occurs in the region where the product is consumed and lessens the need to use virgin materials that are not produced locally), and, of course, less environmental impact. The circular economy can also give businesses new competitive advantages by opening up new chances for inclusive, diverse, and distributed growth.

ReSOLVE [6] is a framework that has been created to help the transition to circular economy and it includes six actions. These are: regenerate, share, optimize, loop, virtualize and exchange. Every component of the framework is applicable to all built-environment scales. (a) In order to regenerate and restore natural capital, it is important to prioritize preserving, repairing, and boosting ecosystem resilience. (b) Sharing entails maximizing asset use, pooling resource use, and reusing/adapting resources. (c) The primary goals of Optimize include enhancing system performance, extending asset life, reducing resource use, and adopting reverse logistics. (d) By focusing inner loops, remanufacturing and refurbishing items and components, as well as recycling materials, one can maintain materials and products in a cycle. (e) Virtualization entails replacing physical resources with virtual ones, virtual services with real ones, physical locations with virtual ones, and remote service delivery. Shared business concepts become especially important in this situation. In order to assure flexible and optimum user-focused designs, (f) exchange uses new business models, flexible design and use, leasing, and performance-based approaches. Additionally, this entails using alternate material inputs in construction, offering service-centric models, and applying cutting-edge technology where necessary. Figure 2-2 summarizes the ReSOLVE framework.

[1] https://ellenmacarthurfoundation.org/topics/circular-economy-introduction/overview

Figure 2-2: ReSOLVE framework

Circular business model framework (Accenture)

Accenture's framework [7] classifies Business Models (BMs) according to their purpose inside the CE and displays the product outcome of such a BM after examining 120 business cases that result in resource productivity increases around the globe. Accenture (2014) offers 11 sub-models and five separate circular BM types: (a) a "made to last" philosophy and a circular supply chain based on the utilization of renewable energy, bio-based products, or recyclables; (b) sharing tools that support cooperative ownership, access, or usage paradigms; (c) the product as a service concept maintains product ownership while providing access to items or performance; (d) product life extension model describes methods for extending a product's lifespan, including upgrades, repairs, resale, and remanufacturing; (e) The resource recovery model focuses on extracting resources or energy from trash or by products. Notwithstanding the five BMs listed by Accenture (2014), the classification ignores BMs for delivering things virtually rather than physically, such as virtualization or dematerialization, as well as BMs for reducing waste. It also ignores BMs for enhancing product performance or efficiency.

Circular Business Model strategies (Bocken et al.)

The types of BM improvements for the CE to slow, narrow, and close resource cycles are presented by Bocken et al. (2016) [8]. The types of slowing resource loops are as follows: (a) models of access and performance that emphasize delivering the capacity or service to satisfy consumers' demands without forcing them to physically own the goods; (b) extending product value entails re-manufacturing procedures or return policies aimed at maximizing a product's residual worth, (c) classic long-life models focus on providing long-lasting and repairable products, and (d) according to the encourage sufficiency model, businesses should adopt a non-consumerism stance and offer items that are long-lasting, upgradeable, serviceable, warrantable, and reparable in order to assist consumers in reducing their consumption. The BM approach for closing resource loops also includes, e) exploiting a resource's remaining worth is known as prolonging its value. Although it groups BMs from a standpoint of slowing and closing resource loops, this classification technique ignores discussing issues like circular inputs and cooperative consumption approaches. To fill in the gaps in this CBM classification, some researchers combine BMs such as "intensifying" and "dematerializing" (Geissdoerfer et al., 2020) [9] and "regenerating" and "informing" (Konietzko et al., 2020) [10] into this strategy in addition to the parts already mentioned.

Business models for circular economy (British Standard Institute)

The British Standard Institute (BSI, 2017) [11] offers six groups of prospective BMs that are compatible with a CE. (a) A business model known as "product as a service" combines products and services and bases innovation on results, like pay-for-success models and leasing. (b) The goal of the sharing economy or collaborative consumption is to increase the use of underutilized or idle assets. (c) The emphasis of the on-demand approach is on offering the good or service solely upon consumer request. (d) Dematerialization stresses replacing physical items with virtual ones. (e) The goal of the product life cycle extension models is to increase the lifespan of a product by designing it to be durable, modular, reusable, adaptable, repairable, and re-manufacturable. (f) Recovery of secondary materials emphasizes recovering and recycling secondary materials and by-products in addition to enticing customers to return unwanted goods. The majority of CBMs are included by this classification, but it leaves out BMs that promote circular inputs, such as using waste products from one operation as input for another (a practice known as industrial symbiosis), renewable energy, and bio-based and recyclable resources.

In this context, a recent study carried out by Atasu et al. [12] go on to say that manufacturing firms, from those that make goods for the new economy to those that produce our apparel and furnishings, can develop a circular business model in a variety of ways. The majority combine three fundamental tactics: (a) Retain Product Ownership (RPO). In the traditional implementation of this strategy, the producer instead chooses to rent or lease the customer's product. As a result, once consumers are done using a product, the maker is still accountable. RPO is an intriguing marketing tactic for businesses who provide complicated products with significant embedded value. One such example is Xerox, which has long leased its printers and photocopiers to business clients. This approach could require businesses to make significant investments in their after-sales and maintenance skills, which might be more expensive for them and, ultimately, their clients than a sell-and-replace approach. When simpler products are somewhat pricey and infrequently used, RPO can be used with them as well. (b) Product life extension (PLE). By concentrating on creating items that last longer, businesses using this strategy may create opportunities for marketplaces in second hand goods. This may appear to be a poor idea for original equipment manufacturers because a longer product lifecycle results in fewer purchases over time. But, longevity is a crucial competitive distinction and offers a compelling case for premium pricing. Moreover, PLE can assist businesses in keeping clients from switching to a competing product. (c) Design For Recycling (DFR). Businesses that utilize this technique adapt their goods and production procedures to maximize the amount of recovered materials that can be used to create new products. Partnering with businesses that have particular technological know-how or who may be best equipped to utilise the materials recovered is a common aspect of this strategy.

The business models proposed above refer to a series of operational strategies, the main model of which is called 9R's circular economy framework [13]. The 9R's are a framework for a circular economy that looks at ways to use and reuse resources to the fullest extent possible while reducing waste and harm to the environment. Refusal, Rethinking, Reducing, Reusing, Repair, Refurbishment, Remanufacturing, Repurposing, Recycling, and Recovery are the verbs. Three different hierarchical methods can be used to close material loops; a smaller loop is preferable because it requires fewer inputs and gets rid of waste before it even arises. The 9Rs can lead us away from a throwaway culture and toward sustainable systems, despite the fact that the transition to a completely circular economy devoid of waste is exceedingly challenging to accomplish. A graphical representation of the strategies and hierarchical levels is presented in Figure 2-3.

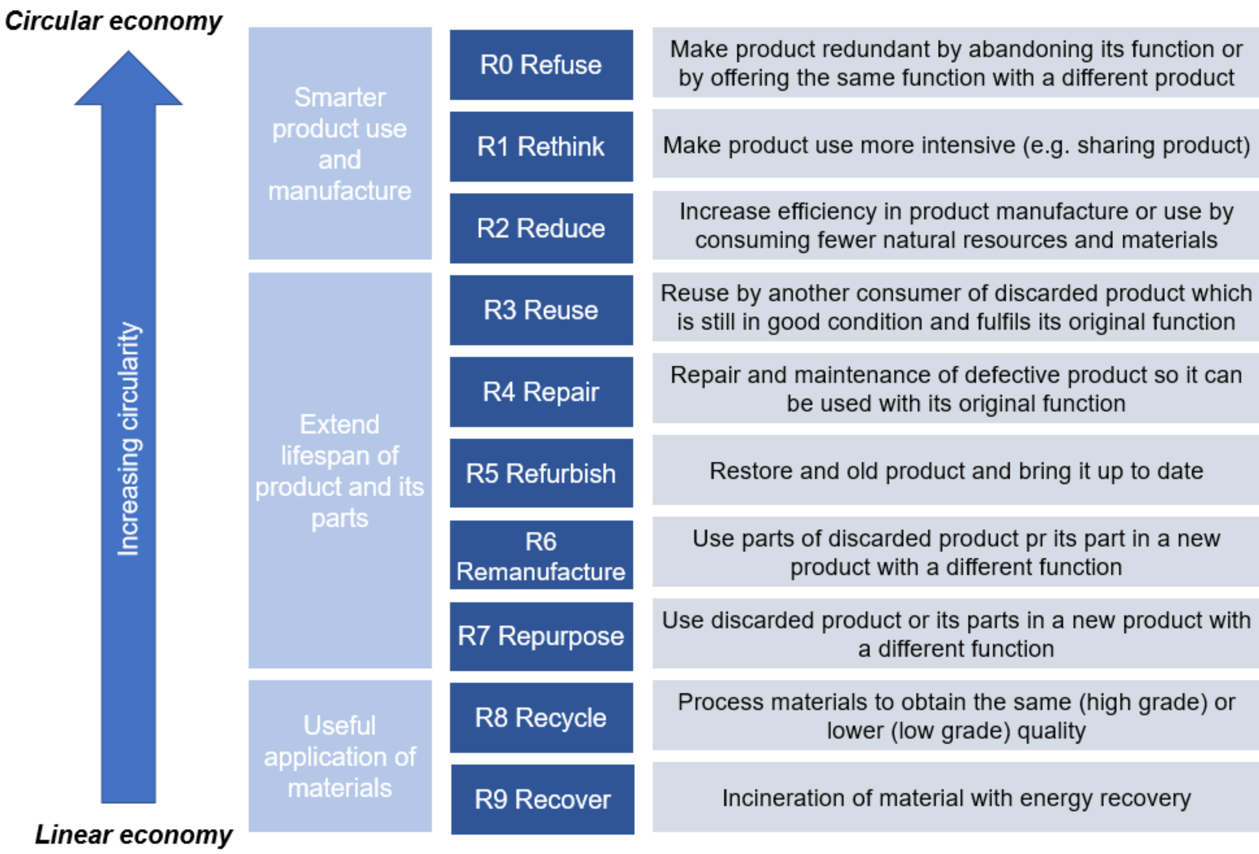

Figure 2-3: 9R's framework

2.3 State-of-the-art of circular economy indicators

The dimension of circularity has been examined for its measurement capabilities through a comprehensive examination of existing circular indicators in the literature. Measuring circularity is a prerequisite for achieving concrete actions and achieving measurable results in the transition to a circular economy. For this reason, numerous initiatives are currently underway nationally and internationally on this topic.[2] The purpose of the literature review was to identify a set of suitable circularity indicators that can support the quantitative research activities of the Circular TwAIn Project. A first input for the activity was a list of circularity indicators created in 2022 retrieved from the Treasure Project [1], a relevant initiative funded by the European Union's Horizon 2020 research and innovation programme. In this Project 6 literature reviews were analysed to access papers, reviews, and works from institutions and consulting agencies that focus on measuring the circular economy at the material, product, company, and national levels.

Starting from that list, an additional examination of the literature has been done using the following keywords "circular economy," "circularity," "indicators," "metrics," "assessment," "evaluation," and "measuring." After avoiding double counting of indicators from the initial list and the new literature review, 109 indicators were collected, including online, excel spreadsheet and analytical tools, which are classified according to the categorisation presented in the following section.

2.3.1 Design of a first set of filtering logics

The classification of indicators for this deliverable, which is presented in Table 2-1 below, is based on the categorisation provided in (Saidani, Yannou, et al., 2019) [14].

Table 2-1: Classification of indicators proposed

Classification field	What it defines?
Description	Definition of the indicator and its working principles
Evaluation method	Type of assessment approach provided by the indicator (i.e., qualitative or quantitative approach)
Dimensionality	Number of outputs provided by the indicator (i.e., single indicator or set of indicators)
Data required	Overview of required data to calculate the indicators
Evaluation format	Type of formulation of the indicator (i.e., excel spreadsheet tool, web-based tool, analytical formula(s), multi-criteria decision tool)
Purpose	Final usage for which the indicator was developed (i.e., information purpose, helping to understand the situation, e.g., tracking progress, benchmarking, hotspot identification; decision-making purpose, helping to take action for managerial activities, strategies formulation, policy choice; communication purpose, internally on the achievements to the stakeholders, or externally to the public; and learning purpose, e.g., education of workforce, awareness among consumers)

After classifying the list of 109 indicators according to the classification model presented, a first screening was carried out based on both the classification and the suitability of the

[2] *EU Commission (2020) Circular economy action plan.*

indicators to the context and scope of Circular TwAIn. For the first screening of the indicator list, only those indicators with taxonomy fields "Evaluation method" and "Evaluation format" classified as "quantitative" and "analytical formula(s)" were considered, meaning only indicators that provide measurable outputs.

Among this sub-set, a second screening was carried out considering the reasonable availability of data required for the calculation of those indicators at pilots level. As a result of this screening, 24 indicators were selected and following listed in Table 2-2; the list of circularity indicators with all the information related to the classification presented can be found in Annex I.

Table 2-2: Circularity indicators

Circularity Indicators	Description (working principles)
Product-Level Circularity Metric (PCM)	C = economic value of recirculated parts / economic value of all parts; where circularity (C) is defined as the fraction of a product that comes from used products (i.e. from closed- or open-looped cycles).
Circular Economy Index (CEI)	Ratio between the material value obtained from recycled products and the one entering the recycling facility (CEI measures circularity in terms of the ratio of recycled material value from EoL products compared to total material value in recycling processes needed to produce new versions of the same product.) (Measures recycling rates, excluding all other circular economy effects and loops).
Circularity Index (CI)	Formula: α = recovered end-of-life (EOL) material / total material demand; β = 1 – energy required to recover material / energy required for primary production; Circularity Index (CI) = αβ, maximum value = 1.
Recycling indicator set: Weight recovery of target material(s) (IW)	IW is an indicator on effectively recovered weight is proposed that is calculated as the sum of the weights of the target materials in each recycled output fraction divided by the total material weight of the input.
Recycling indicator set: Recovery of scarce materials (IS)	IS is an indicator that reflects the criticality of recycled target materials in relation to the total criticality of materials present in the input of the recycling process.
Recycling indicator set: Closure of material cycles (IC)	IC is an indicator to measure material cycle closure.

Recycling indicator set: Avoided environmental burdens (IE)	IE ha the objective to assess the avoided environmental impact that can be achieved by recycling materials.
Recyclability Benefit Rate (RBR)	This indicator is defined as the ratio of the potential environmental savings that can be achieved from recycling the product over the environmental burdens of virgin production followed by disposal.
Material Reutilization Score (MRS)	Indicator showing the content of recycled or recyclable material in a product.
Value-based Resource Efficiency Indicator (VRE)	It aims at introducing the economic value of the materials embedded in consumers products as the property to be measured and accounted.
End-of-life Indices: Reuse index	The Reuse index considers the possibility of a given component being reused in the same product or in similar products.
End-of-life Indices: Remanufacture index	The Remanufacture index evaluates the possibility of a component being regenerated on the basis of different cost types and revenues involved in the 'remanufacture loop'.
End-of-life Indices: Recycling index	The Recycling index compares the difference between the production costs for virgin materials and the revenues coming from the recycling process. In particular, it takes into account the energy savings resulting from the recycling process of a material and the revenues from recycled material.
End-of-life Indices: Incineration index	The Incineration index establishes whether particular combinations of materials can be directly incinerated for energy production.
Sustainablr Circular Index (SCI)	The Sustainable Circular Index is for an individual company and is formed by four dimensions (economic, social, environmental, and circularity).
Linear Flow Index for Product Families	Measures the proportion of material flowing linearly, that is, from virgin materials and up to unrecoverable waste.
Combination Matrix (CM): Circularity	Combination matrix is a matrix that combines the circularity and longevity of a product. Circularity is expressed as the number of times a resource is used in a product system.

Combination Matrix (CM): Longevity	Combination matrix is a matrix that combines the circularity and longevity of a product. Longevity is the length of time that a resource is used.
Effective Disassembly Time	Indicator expressing the effective disassembly time of a product.
Old scrap Collection Rate (CR)	The CR express how much of the end-of-life material is collected and enters the recycling chain.
Circularity of Material Quality (QC)	The material quality indicator is based on the energy use of recycled products versus their counterparts produced from primary material inputs only. It cover the environmental pillar of the sustainability.
Circular-process feedstock intensity (CPFI)	It quantifies raw material consumption and is the ratio of the total amount of the main raw materials used to the total amount of useful outputs.
Circular-process waste factor (CPWF)	It measures the ratio of the total mass (kg) of solid, liquid or gaseous waste, generated as process wastes or lost from the system via leaks or spills, with respect to the total mass (kg) of the end-product and co-products.
Resource efficiency indicator for electrical and electronic equipment (RE EEE)	Resource efficiency not only related to the mechanical technology, but also has a relation with the used condition from human beings. Considering environmental impacts along with utilization of resources, the coefficient of environmental impacts defined before need to be covered while evaluate resource efficiency.

As mentioned in the introduction Section 2.1, next selection round, which will be described in detail in D3.4, aims to map the actual needs/requirements from industrial use cases with the starting indicators' list, thus providing a pilot-specific subset of indicators supporting the measurement of circularity of the key processes in the Circular TwAIn context, considering both research and industry perspectives.

3 Trustworthy AI and collaborative intelligence background

Artificial Intelligence (AI) and Collaborative Intelligence (CI) are two rapidly evolving fields that have the potential to revolutionize the way we live and work. AI refers to the development of computer systems that can perform tasks that would normally require human intelligence, such as recognizing speech or images, making decisions, or learning from data. On the other hand, CI is a new paradigm that combines the strengths of both human and artificial intelligence to achieve better results in problem-solving and decision-making. Several aspects of AI and CI that can have a significant impact on promoting circular economy, including: *(i)* resource optimization, where AI and CI are used to optimize the use of resources and reduce waste in manufacturing and supply chain processes (e.g., predictive maintenance and process optimization algorithms can reduce equipment downtime and energy consumption; demand forecasting models can help prevent overproduction and reduce waste); *(ii)* sustainable design, where AI and CI serve as assistants in designing products and processes that are more sustainable (e.g., generative design algorithms can optimize product designs for reduced material usage); *(iii)* recycling and waste management, in which AI and CI can improve the efficiency and accuracy of recycling and waste management processes (e.g., computer vision algorithms identify and sort different materials for recycling); *(iv)* consumer behaviour, where AI and CI can be exploited to promote more sustainable consumer behaviour by providing personalized recommendations and feedback (e.g., smart home systems can optimize energy usage based on user behaviour, while smart shopping assistants can suggest more sustainable product choices).

Overall, the potential impact of AI and CI on promoting circular economy is significant, and continued investment in research and development in these areas can help accelerate progress towards a more sustainable future. While the benefits of AI and CI are numerous and evident, there are also concerns about their potential negative impacts, particularly in relation to trustworthiness. Trustworthy AI is characterized by its ability to operate in a reliable, transparent, and ethical manner, while safeguarding fundamental human values and rights. Similarly, trustworthiness in CI requires ensuring that the collective intelligence of human and machine participants is developed and used in a manner that is fair, transparent, and promotes the well-being of all stakeholders involved.

Achieving trustworthy AI and CI requires a multidisciplinary approach that involves not only computer scientists and engineers but also experts in ethics, law, and social sciences, and other related fields. Collaborative efforts can bring different perspectives to the table, help identify potential biases, and ensure that ethical considerations are integrated into the development process. Moreover, interdisciplinary collaboration can also facilitate communication and transparency, both of which are essential for building trust between AI developers, stakeholders, and end-users. By involving diverse stakeholders throughout the development process, including those who are affected by the technology, AI developers can ensure that the system is designed with their needs and values in mind. This can ultimately lead to better outcomes for all involved and increase public trust in AI.

While ethical AI development is important, it cannot rely solely on voluntary actions by AI developers. Regulations and policies play a critical role in promoting ethical and trustworthy AI by establishing clear standards and expectations for AI development and use. These may include regulations around data privacy and protection, algorithmic transparency and explainability, bias mitigation, and accountability mechanisms. By setting clear standards and expectations for AI developers and users, regulations and policies can help ensure that AI is developed and used in a way that promotes societal and environmental well-being. Additionally, regulations and policies can help to address the power asymmetry between AI developers and users by ensuring that AI is developed and used in a way that aligns with the interests of all stakeholders, not just those of the developers or users. This may involve incorporating stakeholder input and feedback into the development process, as well as creating mechanisms for public oversight and accountability. Finally, regulations and policies can help to promote international cooperation and coordination around AI development and use. As AI technologies become increasingly global in scope, it is important to establish common ethical standards and guidelines that can be applied across different countries and regions. By working together to promote ethical and trustworthy AI development, policymakers can help to ensure that AI benefits all of humanity, rather than just a select few. To this end, a growing number of initiatives, guidelines, and standards have been developed to promote trustworthy AI and CI. For example, the European Commission has released the Ethics Guidelines for Trustworthy AI, which provides a set of seven key requirements for ensuring AI operates in a trustworthy manner. Similarly, organizations like the Institute for Ethical AI and Machine Learning and the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems have developed standards and best practices for ensuring ethical and trustworthy AI and CI. These guidelines are discussed in Section 3.1.

In addition to these guidelines and standards, there are also technical solutions being developed to promote trustworthy AI and CI. For example, explainable AI (XAI) is an approach to developing AI systems that can provide clear and understandable explanations for their decision-making processes, which can increase transparency and accountability. Similarly, federated learning is a technique for training AI models on decentralized data sources, which can help preserve privacy and prevent bias.

As AI and CI continue to evolve and become more integrated into our daily lives, ensuring their trustworthiness will be essential for building and maintaining public trust and confidence in these technologies. This will require ongoing collaboration and dialogue between stakeholders in academia, industry, government, and civil society, as well as continued investment in research and development of trustworthy AI and CI solutions. To ensure that AI is developed and deployed in a way that is ethical and trustworthy, it is important to build a culture of ethical AI within organizations. This requires training and education programs for employees and stakeholders, as well as a commitment to transparency, accountability, and ethical decision-making. This can help organizations build trust and credibility among users and stakeholders and avoid potential ethical and reputational risks associated with AI.

3.1 Building trust in human-centric AI: EU Guidelines

Trustworthy AI refers to the development and deployment of AI systems that are designed to operate in a manner that is transparent, reliable, and ethical. In other words, it is an approach to AI that seeks to ensure that these systems are safe, fair, and aligned with human values. the European Commission has released several recommendations and guidelines for the development and deployment of trustworthy AI systems. The most significant of these is the "Ethics Guidelines for Trustworthy AI", which was published in

2019 by the European Commission's High-Level Expert Group on AI[3]. The Ethics Guidelines for Trustworthy AI provide a framework for ensuring that AI systems are developed and deployed in a way that is ethical, transparent, and respects fundamental human rights. The guidelines outline seven key requirements for trustworthy AI, which are discussed in the following sections.

3.1.1 Human agency and oversight

AI systems should be designed to enhance human decision-making, not replace it. Humans should be able to understand and control AI systems, and there should be a clear process for human review and intervention. Improving human agency and oversight in AI algorithms requires designing and implementing AI systems in a way that allows for human control and intervention. In the context of CI, human oversight and accountability play a key role since humans are actively involved in key decision-making processes. AI systems are very powerful tools in automating decision-making, but they should not replace human judgment or responsibility. Human oversight and accountability are essential for ensuring that AI systems are used in a responsible and ethical manner. This requires the involvement of human decision-makers in key decision-making processes, as well as the development of appropriate mechanisms for monitoring and evaluating the performance of AI systems. Some specific steps to take for improving human agency and oversight in AI algorithms include:

- Involve human experts in the design and development process: Bring in domain experts who can provide valuable insights into how the AI system will be used and who can help identify potential areas of concern. This will ensure that the AI system is designed with human oversight in mind.
- Build in mechanisms for human control and intervention: AI systems should be designed in a way that allows humans to intervene when necessary. For example, you might include mechanisms for human review and approval of decisions made by the AI system or build in the ability for humans to override decisions made by the system.
- Ensure transparency and explainability: AI systems should be transparent and explainable so that humans can understand how they are making decisions. This will make it easier for humans to identify when intervention is necessary and to take corrective action.
- Conduct regular audits and evaluations: Regular audits and evaluations of the AI system can help ensure that it is performing as expected and that any issues are identified and addressed in a timely manner.
- Develop clear policies and procedures: Clearly defined policies and procedures can help ensure that humans understand their roles and responsibilities when it comes to overseeing and controlling the AI system. This can include things like defining who

[3] https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

is responsible for making decisions and what the process is for intervening when necessary.

3.1.2 Technical robustness and safety

Safety and reliability concerns of AI systems deserve an equal understanding of implications and negative impacts, especially for autonomous AI systems. Autonomous systems such as self-driving cars or robots can raise ethical concerns related to safety, liability, and human oversight. To ensure that these systems are trustworthy and ethical, developers must pay close attention to issues such as safety and reliability, human oversight and control, and potential societal impacts. Improving technical robustness and safety in AI algorithms involves designing and developing the algorithm in a way that ensures it is reliable, secure, and resilient. The following steps should be considered to ensure the technical robustness and safety in AI algorithms:

- Test and validate the algorithm thoroughly: Rigorous testing and validation are crucial to ensure that the algorithm is performing as expected and is resilient to unexpected situations. A variety of methods is available, including unit testing, integration testing, and end-to-end testing, to verify the algorithm's functionality and performance.
- Address potential security vulnerabilities: AI algorithms can be vulnerable to security threats, so it is important to address potential vulnerabilities throughout the development process. This can include measures such as secure coding practices, penetration testing, and the use of secure communication protocols.
- Implement error detection and correction mechanisms: AI algorithms should be designed with mechanisms for detecting and correcting errors or unexpected behaviour. This can include error logging, automated monitoring, and real-time alerting to notify humans when errors occur.
- Ensure transparency and explainability: AI algorithms should be transparent and explainable so that humans can understand how they are making decisions. This can make it easier to identify and correct errors or unexpected behaviour.
- Implement version control and change management processes: AI algorithms can be complex, and it's important to have a clear process for managing changes and updates to the algorithm. This can include version control, change management processes, and release management practices.

3.1.3 Privacy and Data governance

Training good AI systems require often large amounts of data, in some cases also personal data (e.g., to predict the physical or mental stress of workers, physiological data are required for training the AI algorithm). Gathering personal data raises concerns about data privacy and protection per se, demanding for proper data governance and cybersecurity measures to put in place to protect personal information and prevent data breaches. This requires attention to issues such as data minimization, encryption, and access control, as well as the use of appropriate privacy and security frameworks and standards, in a way to ensure the compliance with relevant laws and regulations. But also, the application of AI systems themselves, which may predict/derive/infer new pieces of information that maybe the targeted people would have preferred not to disclose (e.g., an AI algorithm may infer the health status of a worker, predicting the probability of having certain diseases, given people's personal data). It is thus important to consider the ethical aspects of developing and deploying autonomous AI systems. Some mitigation actions to consider when coping with privacy and data governance are the following:

- Minimize data collection: Collect only the minimum amount of data necessary to train and operate the algorithm. This can help reduce the risk of unauthorized access, accidental disclosure, or misuse of personal data.
- Use secure data storage and transmission methods: Personal data should be stored securely and transmitted using encrypted communication channels to prevent unauthorized access or disclosure.
- Implement data access controls: Access to personal data should be restricted only to authorized personnel who require access to perform their job duties. Role-based access control and authentication should be adopted to ensure that only authorized personnel can access personal data.
- Develop clear policies for data retention and deletion: Personal data should only be retained for as long as necessary to fulfil the purposes for which it was collected. You can develop policies for data retention and deletion that specify how long data will be retained and under what circumstances it will be deleted.
- Ensure transparency and explainability: AI algorithms should be transparent and explainable so that individuals can understand how their personal data is being used. You can provide clear explanations of how data is collected, stored, and used, as well as information about the algorithm's decision-making processes.
- Comply with relevant laws and regulations: Ensure that your AI algorithm complies with relevant laws and regulations, such as the General Data Protection Regulation (GDPR).

3.1.4 Transparency

To clarify the rationale behind AI decisions and bring to light potential biases or discriminations, transparency and explainability of AI systems should be considered. The transparency and explainability are important because they help in building trust and understanding among AI and CI human users. Especially when supporting humans in decision-making, users need to know how an AI system is making decisions, what data are being used, and what criteria are being considered to evaluate outcomes. This helps also in addressing accountability; indeed, users and stakeholders can hold AI developers and operators responsible for any potential errors or issues that may arise. Specific guidelines to improve transparency in AI algorithms include the following:

- Document the algorithm's design and development process: Documenting the algorithm's design and development process can help ensure that its decision-making processes are transparent and explainable. Useful methods include flowcharts, diagrams, and written descriptions to document the algorithm's logic and decision-making processes.

- Provide explanations of how decisions are made: AI algorithms should be designed to provide explanations of how they arrive at their decisions. Some AI algorithms are explainable "by nature", such as decision trees, rule-based systems. Natural language explanations may help in providing clear and understandable explanations of how the algorithm arrived at a particular decision.
- Prefer interpretable models: Using interpretable models, such as decision trees or linear models, can help make the algorithm's decision-making processes more transparent and explainable. These models can be easier to interpret and explain to humans than more complex models, such as deep neural networks.
- Provide access to relevant data: Providing access to relevant data, such as training data or input data, can help humans understand how the algorithm is making decisions. This can include providing access to training data sets or log files that show how the algorithm is processing data.
- Ensure transparency in model updates and changes: When making updates or changes to the algorithm, it is important to ensure that these changes are transparent and explainable. This can include documenting changes to the model or providing clear explanations of how the updates will impact the algorithm's decision-making processes.

3.1.5 Diversity, non-discrimination, and fairness

It is of utmost importance to consider fairness and non-discrimination in AI decision-making, which are mainly affected by potential biases in data, algorithms, and outcomes. Indeed, AI systems are as good as the data they are trained on; if data contain biases, or lack diversity, the resulting AI algorithms will perpetuate those biases. It is crucial to ensure that AI is developed and deployed in a way that is fair and non-discriminatory, with a focus on improving equity and inclusivity. This requires attention to issues such as data quality, representation, and diversity, as well as the use of appropriate algorithms that are designed to prevent biases.

To address these aspects, AI developers should consider the following guidelines:

- Ensure diversity in the data used to train the algorithm: The data used to train the algorithm should be diverse and representative of the population that the algorithm will be applied to. This can help prevent biases and ensure that the algorithm is fair and non-discriminatory.
- Identify and mitigate potential biases in the algorithm: Identify potential biases in the algorithm, such as overrepresentation or underrepresentation of certain groups, and mitigate them. Methods such as debiasing are useful to address biases in the algorithm.
- Monitor the algorithm for potential biases: Continuously monitor the algorithm for potential biases, such as disparate impact on certain groups, and take corrective action if necessary.
- Involve diverse stakeholders in the development process: Involve diverse stakeholders, including individuals from underrepresented groups, in the

development process to ensure that the algorithm is designed and developed with diversity and inclusivity in mind.

- Evaluate the algorithm's impact on diversity, non-discrimination, and fairness: Evaluate the algorithm's impact on diversity, non-discrimination, and fairness to identify areas for improvement and ensure that the algorithm is achieving its intended goals.

3.1.6 Societal and environmental well-being

AI may impact on social and environmental well-being, also including how to ensure AI supports sustainable development goals. While AI has the potential to contribute to social and environmental well-being, it can also exacerbate existing social and environmental challenges. For this reason, AI should be developed and deployed in a way that supports sustainable development goals, by reducing the negative social and environmental impacts. Relevant aspects to address for mitigating negative effects include social and environmental justice, fairness, and inclusivity. Also, AI developers should consider the adoption of appropriate tools and frameworks to measure and evaluate the impact of AI. To account societal and environmental well-being in AI algorithms, the following actions help in considering the impact the AI algorithm will have on society and the environment:

- Consider the broader impact of the algorithm: Consider the broader impact of the algorithm on society and the environment, including potential unintended consequences. This can include assessing the impact on different stakeholder groups, including marginalized or vulnerable populations, and evaluating the environmental impact of the algorithm.
- Design the algorithm to promote societal and environmental well-being: Design the algorithm to promote societal and environmental well-being, such as by prioritizing energy efficiency or reducing waste. You can also consider incorporating social and environmental impact metrics into the algorithm's design and development process.
- Engage with stakeholders to understand their needs and concerns: Engage with stakeholders, including community groups and environmental organizations, to understand their needs and concerns regarding the algorithm's impact on society and the environment. This can help ensure that the algorithm is designed and implemented in a way that addresses their concerns.
- Evaluate the algorithm's impact on societal and environmental well-being: Evaluate the algorithm's impact on societal and environmental well-being, and use this information to identify areas for improvement and ensure that the algorithm is achieving its intended goals.

3.1.7 Accountability

Improving accountability in your AI algorithm involves designing and developing the algorithm in a way that ensures transparency and accountability for its actions and outcomes. In order to ensure that AI systems remain ethical and trustworthy over time, it is important to establish monitoring and accountability mechanisms. This may involve setting up regular audits or reviews of AI systems, as well as creating systems for reporting and addressing any ethical concerns or issues that arise. Additionally, accountability mechanisms may include establishing clear lines of responsibility and liability for AI systems and their outputs, as well as providing avenues for redress or remedy in the case of harm caused by an AI system. In the following, some specific steps to take for improving accountability in AI algorithms are reported:

- Clearly define the purpose and goals of the algorithm: Clearly define the purpose and goals of the algorithm, including its intended outcomes and any potential risks or unintended consequences. This can help ensure that the algorithm is developed with a clear sense of accountability.
- Document the algorithm's development and implementation process: Document the algorithm's development and implementation process, including the data used to train the algorithm and any decisions made throughout the process. This can help ensure transparency and accountability for the algorithm's actions and outcomes.
- Establish clear roles and responsibilities for the development and use of the algorithm: Establish clear roles and responsibilities for the development and use of the algorithm, including who is responsible for monitoring the algorithm and addressing any issues that arise.
- Implement feedback mechanisms: Implement feedback mechanisms to enable stakeholders to provide feedback on the algorithm's performance and use this feedback to improve the algorithm over time.
- Monitor and evaluate the algorithm's performance: Continuously monitor and evaluate the algorithm's performance, including its impact on different stakeholder groups and any unintended consequences. Use this information to improve the algorithm and ensure that it is achieving its intended goals.

3.2 Other relevant frameworks and initiatives

In the scope of European effort to propose guidelines and promote standards, some other initiatives have been started. Some of them, e.g., the AI Act, also form the basis for the applicable law and regulations. We briefly discuss the most relevant in the following sections.

3.2.1 AI Act

*T*he AI Act is a legislative proposal from the European Commission that aims to establish a harmonized regulatory framework for AI across the European Union (EU).[4] The AI Act proposes a risk-based approach to regulating AI, with different requirements and obligations depending on the level of risk posed by the AI system. The proposal defines four levels of risk, ranging from “unacceptable risk” to “minimal risk,” with corresponding regulatory requirements and obligations for each level.

Some of the key provisions of the AI Act include:

[4] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52021PC0206

- Prohibition of certain high-risk AI systems: The proposal includes a ban on certain AI systems that are considered to pose an unacceptable level of risk, such as AI systems that are used for social scoring or real-time biometric identification.
- Requirements for high-risk AI systems: AI systems that are considered to pose a high level of risk will be subject to strict requirements, including mandatory conformity assessments, documentation requirements, and transparency obligations.
- Transparency obligations: AI systems must be transparent and explainable, and users must be provided with clear information about how the system operates and how decisions are made.
- Data protection and privacy: The AI Act includes provisions to ensure that AI systems are designed to protect user data and privacy, and that data is collected, processed, and used in a way that is consistent with EU data protection laws.
- Liability: The proposal includes provisions for determining liability in cases where an AI system causes harm or damage.

The AI Act is expected to have a significant impact on the development and deployment of AI systems in the EU, and it represents a significant step towards establishing a harmonized and comprehensive regulatory framework for AI.

3.2.2 ISO standards and technical reports

In recent years, efforts underway to develop international standards for trustworthy AI have been carried out. The International Organization for Standardization (ISO) has established a dedicated committee, ISO/IEC JTC 1/SC 42, to develop standards for AI and other emerging technologies. The committee worked on a series of standards related to trustworthy AI, including:

- ISO/IEC TR 24028:2020:[5] Overview of trustworthiness in artificial intelligence: the document analyses the most important factors that may impact the trustworthiness of AI systems. The document reports on existing approaches that can improve trustworthiness in technical systems, and suggests possible mitigation strategies to address AI system vulnerabilities that relate to trustworthiness.
- ISO/IEC 24368:2022:[6] Overview of ethical and societal concerns: This standard provides a high-level overview of AI ethical and societal concerns, and provides information in relation to principles, processes and methods in this area. The document is intended for technologists, regulators, interest groups, and society at large, and it includes many pointers to other International Standards that address issues arising from AI ethical and societal concerns.
- ISO/IEC 23894:2023:[7] Guidance on risk management: this standard provides guidance on risk management, proposing a framework to assist the organization in integrating risk management into significant activities and functions.

[5] https://www.iso.org/obp/ui/#iso:std:iso-iec:tr:24028:ed-1:v1:en
[6] https://www.iso.org/obp/ui/#iso:std:iso-iec:tr:24368:ed-1:v1:en
[7] https://www.iso.org/obp/ui/#iso:std:iso-iec:23894:ed-1:v1:en

3.2.3 BDVA Task Force 11: Trustworthiness of Industrial AI

The Big Data Value Association (BDVA) has established a task force, called Task Force 11 (TF11),[8] to develop a set of guidelines for trustworthy AI. The focus of TF11 is on AI research, innovation and deployment, also in relation to industrial data and the consequent AI trustworthiness. TF11 purpose is to accelerate the adoption of Industrial and Trustworthy AI in Europe, and it supports the EU policy framework and efforts to foster digital economy and industrial development. TF11 also publishes responses to public consultations on ethical and legal requirements for AI.[9] In the European context, TF11 is another player actively involved in steering the application of trustworthy AI in industries.

3.2.4 Focus group on Environmental efficiency for AI and other emerging technologies (ITU)

In 2019, the ITU-T Study Group 5 established the ITU-T Focus Group on "Environmental Efficiency for Artificial Intelligence and other Emerging Technologies" (FG-AI4EE)[10] in Geneva. The focus group aims to identify standardization needs to develop a sustainable approach to emerging technologies, such as AI, automation, smart manufacturing, and more. The FG-AI4EE develops technical reports and specifications that address the environmental efficiency, as well as water and energy consumption of these technologies, with the goal of providing guidance to stakeholders on how to operate them in a more sustainable manner. The ultimate objective is to help meet the 2030 Agenda for Sustainable Development and its 17 Sustainable Development Goals. The focus group serves as an open platform for various stakeholders, including policy makers, researchers, engineers, representatives of vertical industries, regulators, practitioners, entrepreneurs, service providers, platform providers, network operators, international organizations, industry forums, and consortia. By sharing knowledge, best practices, and lessons learned, the focus group hopes to promote a more sustainable approach to emerging technologies and contribute to a circular economy.

3.2.5 The Institute for Ethical AI and Machine Learning

The Institute for Ethical AI & Machine Learning (IEML)[11] is a UK non-profit organization that aims at promoting ethical and responsible development and use of AI and machine learning technologies. It provides a platform for researchers, developers, and policymakers to collaborate and share knowledge on ethical issues related to AI. The framework revolves around 8 principles of responsible ML development:

- Human augmentation: The impact of inaccurate predictions in the automation process must be considered when implementing machine learning systems. Technologists should understand the consequences of incorrect predictions, especially in critical processes that can greatly affect human lives. However, the consideration should not be limited to critical use-cases. Subject-domain experts

[8] https://www.bdva.eu/task-force-11-trustworthiness-industrial-ai

[9] https://bdva.eu/sites/default/files/BDVA%20response%20to%20the%20public%20consultation%20on%20AI%20ethical%20and%20legal%20requirements.pdf

[10] https://www.itu.int/en/ITU-T/focusgroups/ai4ee/Pages/default.aspx

[11] https://ethical.institute/index.html

should be allowed to review and provide input at the end of machine learning systems to improve overall results.

- Bias evaluation: To create systems that make significant decisions, it's important to acknowledge and reduce the inherent computational and societal bias present in data. Rather than embedding ethics directly into algorithms, technologists should focus on developing processes to identify and document the bias in the data, features, and inference results. This approach allows for domain-specific implications to be addressed, and appropriate processes can be put in place to mitigate potential risks. This is a more practical and effective method to ensure ethical use of AI.
- Explainability by justification: The importance of understanding how complex ML pipelines work internally and investing reasonable efforts to improve tools and processes to explain results based on features and models chosen is emphasized. Adding domain knowledge through features can make ML systems more explainable, even if it decreases accuracy in some cases.
- Reproducible operations: Machine learning systems in production may not be able to effectively diagnose or respond to problems that arise, and there may be a lack of reproducibility in the results. To address this, standard procedures and best practices should be adopted, such as reverting to previous models or reproducing inputs for debugging. Tools and practices for machine learning operations can aid in reproducibility by abstracting computational graphs and archiving data at each step.
- Displacement strategy: The impact of automating medium to large-scale processes affects multiple individuals and requires support for stakeholders to develop a change-management strategy. As technologists, it is important to look beyond the technology and ensure the necessary processes are in place for operational transformation, regardless of the type of work being automated.
- Practical accuracy: To build accurate systems that learn from data, it's important to have a thorough understanding of the underlying means to assess accuracy. Default/basic cost metrics may not be sufficient as what is considered "correct" for a computer may not align with human expectations. To ensure the right challenge is being addressed, it's important to break down metrics from a domain-specific perspective and explore alternative cost functions based on domain-knowledge.
- Trust by privacy: When building large-scale data-driven systems, it is crucial to build trust among stakeholders by informing them about the data, the processes around it, and the importance of protecting it. This can be achieved by enforcing privacy by design and implementing continuous processes to build trust with users and other stakeholders.
- Data risk awareness: Autonomous decision-making systems increase the risk of security breaches, but it's important to recognize that a significant portion of security breaches are caused by human error. To mitigate risks, technologists should focus on educating personnel, establishing processes around data, and assessing the implications of ML backdoors.

3.3 AI in working environments to support Circular Economy

Bringing AI into production environments has the potential to improve efficiency, reduce costs, and increase productivity. However, we highlighted that there are also risks and ethical considerations that need to be addressed to ensure that AI is implemented in a way that is safe, ethical, and respects human rights.

One of the main risks associated with AI is the potential impact on jobs. AI has the potential to automate many tasks that are currently performed by human workers, which could lead to job displacement and changes in the nature of work. To address this risk, it is important to ensure that AI is implemented in a way that supports the well-being of workers, and that strategies are developed to help workers transition to new roles or acquire new skills.

Another risk is the potential for bias and discrimination in AI systems. If AI is used to make decisions about hiring, promotions, or other employment-related matters, there is a risk that the system could inadvertently perpetuate existing biases or discrimination. To address this risk, it is important to ensure that AI systems are developed and trained in a way that is fair and unbiased, and that their decision-making processes are transparent and explainable.

In terms of human rights, it is important to ensure that AI is implemented in a way that respects fundamental human rights, such as the right to privacy, the right to non-discrimination, and the right to fair working conditions. AI systems should be designed and implemented in a way that respects these rights, and mechanisms should be put in place to ensure that the systems are monitored and evaluated for their impact on human rights.

Social and ethical barriers may also exist when implementing AI in working environments. For example, workers may be resistant to the use of AI if they perceive it as a threat to their jobs or if they have concerns about the impact on their privacy. To address these barriers, it is important to involve workers and other stakeholders in the decision-making process and to communicate clearly about the benefits and risks of AI.

Overall, the key to successfully bringing AI into working environments is to approach it in a way that is responsible, ethical, and inclusive, thus following the guidelines and framework discussed in Sections 3.1 and 3.2. This requires a deep understanding of the potential risks and benefits of AI, and a commitment to ensuring that AI is developed and deployed in a way that supports human well-being and respects fundamental human rights. It is thus important to consider the ethical aspects of developing and deploying autonomous AI systems. Ethical implications of AI systems help AI developer in committing to develop AI systems in a way that is beneficial for the society. To this end, safety and reliability concerns of AI systems deserve an equal understanding of implications and negative impacts, especially for autonomous AI systems. Autonomous systems such as self-driving cars or robots can raise ethical concerns related to safety, liability, and human oversight. In the special case of continuous learning and improvement, AI systems are dynamic, and they come with the ability to continuously learn and improve over time. This may involve incorporating feedback loops and other mechanisms for learning from experience and adapting to changing circumstances. Additionally, AI developers should be open to feedback and willing to make changes as needed to ensure that the system remains ethical and trustworthy. This may involve regularly reviewing and updating the system's ethical principles, as well as staying up to date with the latest research and best practices in the field. By prioritizing continuous learning and improvement, AI developers can help ensure that their systems remain relevant and beneficial to society and the environment.

In the scope of circular economy, there are many opportunities and challenges of applying trustworthy AI, also explored in the scientific literature [15], [16], [17]. The use of AI can be beneficial for the transition towards a circular economy by optimizing processes, reducing waste, and enabling more sustainable production and consumption patterns. Here are some common strategies to bring AI to the circular economy:

- Predictive Maintenance: AI can help companies predict when equipment or products may fail, allowing them to repair or replace them before a problem occurs. This can extend the lifespan of equipment and reduce the need for replacements, ultimately reducing waste.
- Resource Optimization: AI can help optimize resource use by analysing data on production processes, supply chains, and consumer behaviour. By identifying areas of inefficiency, AI can help companies reduce waste, minimize resource consumption, and optimize production.
- Circular Design: AI can be used in the design process to create products that are more durable, reusable, and recyclable. By analysing product data, AI can help identify opportunities for product redesign that optimize the use of materials and minimize waste.
- Circular Business Models: AI can support the implementation of circular business models such as product-as-a-service or closed-loop supply chains. By collecting and analysing data on product use and customer behaviour, AI can help companies optimize the use of resources and reduce waste.
- Sustainable Consumption: AI can support sustainable consumption by providing consumers with information on the environmental impact of products, enabling more informed purchasing decisions. AI can also help companies to analyse consumer behaviour and tailor product offerings to reduce waste and support sustainable consumption.

In literature, some concerns have been raised toward the application of AI to support the circular economy. Roberts et al. [18] highlighted how the unethical use of AI presents several plausible risks: potential direct harms from AI systems for CE may occur when data privacy and algorithmic biases are not considered. Indeed, CE concerns relationships and processes between multiple parties, posing a pressing need for cooperative networks, and data and interoperable systems are critical to this end. Also, the proliferation of tracking and measurement devices (e.g., IoT), is often a prerequisite for AI-powered CE products, but this poses significant ethical risk (e.g., to recommend a location for returning a product for remanufacturing, the geospatial data of the customers must be revealed). Automated pricing and other algorithmic business models may amplify disparities when not considering algorithmic biases. For example, using personal characteristics for pricing CE products brings some risks that materialise even when avoiding protected characteristics (e.g., race, gender), because some other attributes may act as “proxies,” (e.g., the inclusion of consumer’s ZIP code as a variable, so as to minimise transport emissions, act as a proxy for ethnicity, because some ethnic groups may live only in certain subareas of cities).

Also, Roberts et al. reported on broader structural considerations of using AI technologies, showcasing how these technologies exacerbated economic inequality and exclusion, but also how some applications are intrinsically risky (e.g., water reuse is an excellent opportunity to apply CE principles, but there are many concerns and unknowns about the impact on human health of the quality of recycled water).

3.4 Assessing and improving the AI trustworthiness: toolboxes and methodologies

Deliverable D1.2 “Ethical Analysis, Governance and Guidelines – 1st version” discusses the ALTAI (Assessment List for Trustworthy Artificial Intelligence) methodology, a list intended for self-assessment to support AI developers, deployers and users in using trustworthy AI. In this deliverable, we focus on frameworks. Toolboxes, and methodology that can help developer from the technical standpoint. Indeed, we report that the interest in toolboxes and kits to support the trustworthiness assessment is rapidly increasing, both in academia [19] [20] and industries. Big tech industries already started defining toolkits to address AI trustworthiness of existing algorithms. These tools are designed to evaluate and improve the transparency, fairness, and reliability of AI systems, following the design principles presented in Sections 3.1 and 3.2. In this section, we briefly discuss some of them as a non-exhaustive “catalogue” of toolboxes that AI developers may consider during Circular TwAIn Project execution.

- **AI Fairness 360**:[12] This is an open-source toolkit maintained by IBM Research Trusted AI, which contains a set of metrics and algorithms for detecting and mitigating bias in AI systems. It includes algorithms for bias detection, bias mitigation, and model explainability. Related projects are **AI Explainability 360**,[13] the toolkit for comprehending ML models predictions, and **AI Privacy 360**,[14] a toolkit for assessing the privacy risks of AI solutions.

- **InterpretML**:[15] This is another open-source toolkit that provides tools for interpreting and explaining machine learning models. It is maintained by the InterpretML Contributors, and it includes several state-of-the-art interpretability algorithms that can be used to understand how a model arrived at a particular decision.

- **What-If Tool**:[16] This is a tool by Google that is useful within notebook environments to inspect AI Platform Prediction models via interactive dashboards. It allows users to visualize and understand the behaviour of machine learning models, and it includes features for visualizing model performance, identifying errors, and debugging models. This tool integrates with TensorBoard, Jupyter notebooks, Colab notebooks, and JupyterHub.

[12] https://aif360.mybluemix.net/
[13] https://aix360.mybluemix.net/
[14] https://aip360.mybluemix.net/
[15] https://interpret.ml/
[16] https://pair-code.github.io/what-if-tool/

- **Fiddler**:[17] Fiddler is an enterprise software platform delivering delivers the best interpretability methods available by combining top explainable AI principles with proprietary solutions for monitoring, analyzing, and diagnosing AI models.
- **Truera**:[18] Truera is a software platform that helps organizations assess the accuracy, fairness, and explainability of their AI models. It includes tools for detecting and mitigating bias and provides detailed reports and visualizations to help stakeholders understand and evaluate model performance. The research division mainly focuses on Data & Model quality, System performance, and Human-centric ML. Results have been also published as academic research outcomes.
- **Awesome Production ML**:[19] this is a repository containing open-source libraries that, among others, help in improving AI explanation and privacy preserving. The repository is maintained by the Institute for Ethical Machine Learning, whose AI principles have been discussed in Section 3.2.5.

These toolboxes and frameworks are designed to help ensure the trustworthiness of AI systems, but it is important to note that they are not a silver bullet. Ensuring trustworthy AI requires a comprehensive approach that includes not only the use of these tools but also a deep understanding of the ethical implications of AI systems and the potential impact on individuals and society. For a more complete list of frameworks and toolkits, the reader may refer to the list[20] regularly updated by AI ethicist, one of the first global repositories of reference and research material on AI ethics.

[17] https://www.fiddler.ai/explainable-ai
[18] https://truera.com/ai-quality-research/trustworthy-ml-research/
[19] https://github.com/EthicalML/awesome-production-machine-learning
[20] https://www.aiethicist.org/frameworks-guidelines-toolkits

4 Circular TwAIn Reference Architecture Background

4.1 Reference Architectures in the Manufacturing Domain

In this section the main Reference Architectures in the industrial domain will be analyzed to define the baseline for the design of the Circular TwAIn Reference Architecture.

The Reference Architectural Model Industry 4.0 (RAMI4.0) [21] has been defined by the Platform Industrie4.0 initiative and standardized through the German DIN standardization body with the DIN SPEC 91345 code.

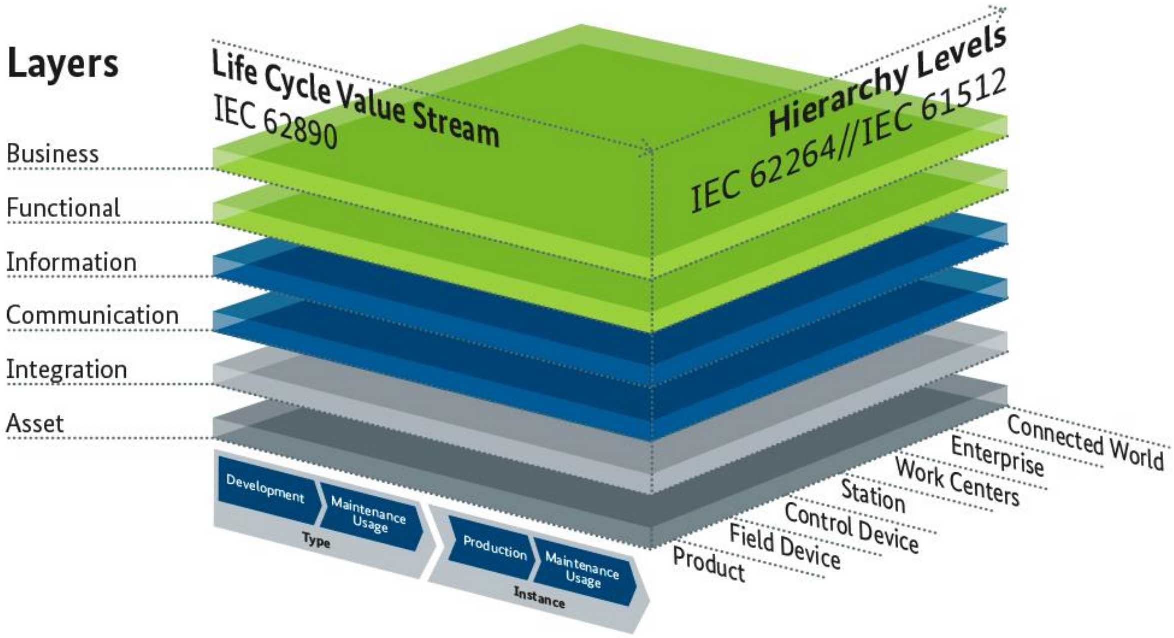

Figure 4-1: RAMI4.0 Model

The main goal is to support the digital transformation in the industrial domain using three dimensions:

- **Architecture Layers** represent six different aspects of business including the organisation of business processes, the aspired functionality of the asset, the output of data, the communication technologies necessary for data generation and treatment, and the development of the asset itself and its connection with digitally controlled processes.
- **Life cycle value stream**. This axis represents a product's lifecycle stage and mainly consists of the development and usage phases. In the development phase, the asset, its production or construction and the possibilities for its maintenance are planned, whereas in the usage phase the asset is produced and identified, with, for example, a serial number, and maintenance and service are ensured.
- **Hierarchy Levels**. This axis reflects the hierarchical structure of the Industry 4.0 network. Since the rather flexible networks can consist of production plants, machines and products belonging to different companies, a consistent hierarchical structure is necessary for network-wide communication.

The Industrial Internet Reference Architecture (**IIRA**) [22] is defined by the Industrial Internet Consortium (IIC), a global initiative of business, government and research organizations. IIRA defines several categorizations, based on the ISO/IEC 42010, the main one introduces four viewpoints: business, usage, functional and implementation. The most relevant is the functional viewpoint, because it specifies a number of different functionalities, which are called functional domains. In this way, ideally an IoT system can be fragmented into “functional domains”, which are the building blocks applicable to domains and applications.

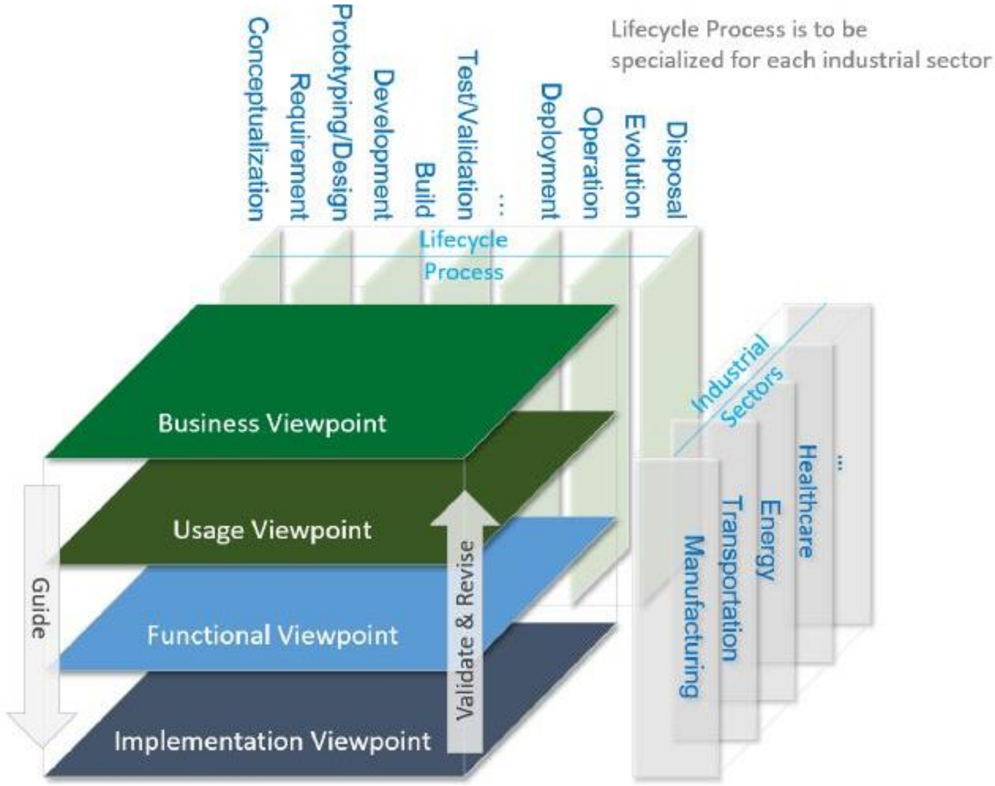

Figure 4-2: IIRA viewpoints

IIRA also refers to several pattern, the most important one is the three-tier architecture pattern that contains following three tiers:

- Edge Tier: Closer to physical world. Collects data from edge nodes. Typically edge tier will be distributed and will be varying based on different usage scenarios. Edge nodes are connected with each other with in proximity network. Example includes Sensors collecting temperature in a building or street or remote volcano.
- Platform Tier: Connects Enterprise tier with Edge tier. It converts the control commands from Enterprise to the format understandable by Edge tier. Receives the data from Edge Tier, processes them and use shared with Enterprise Tier. Data processing includes data cleansing, aggregation and analytics.
- Enterprise Tier: Acts as command center for Edge tier. Typically, applications will be running in Enterprise tier which will receive the data for decision making and flows back control commands to Edge and Platform tier.

Despite RAMI4.0, IIRA doesn’t provide a detailed list of concerns, paving the way for heterogeneous implementation that could be not interoperable one each other.

The International Data Space Reference Architecture Model (**RAM4.0**) [23] aims to define the standards for implementing the data sovereignty including methods for secure data exchange and data sharing. In compliance with common system architecture models and standards (e.g., ISO 42010, 4+1 view model), the Reference Architecture Model uses a five-layer structure expressing various stakeholders' concerns and viewpoints at different levels of granularity:

- The **Business Layer** specifies and categorizes the different roles which the participants of the International Data Spaces can assume, and the main activities and interactions connected with each of these roles.
- The **Functional Layer** defines the functional requirements of the International Data Spaces, plus the concrete features to be derived from these.
- The **Process Layer** specifies the interactions taking place between the different components of the International Data Spaces; using the BPMN notation, it provides a dynamic view of the Reference Architecture Model.
- The **Information Layer** defines a conceptual model which makes use of linked-data principles for describing both the static and the dynamic aspects of the International Data Space's constituents.
- The **System Layer** is concerned with the decomposition of the logical software components, considering aspects such as integration, configuration, deployment, and extensibility of these components.

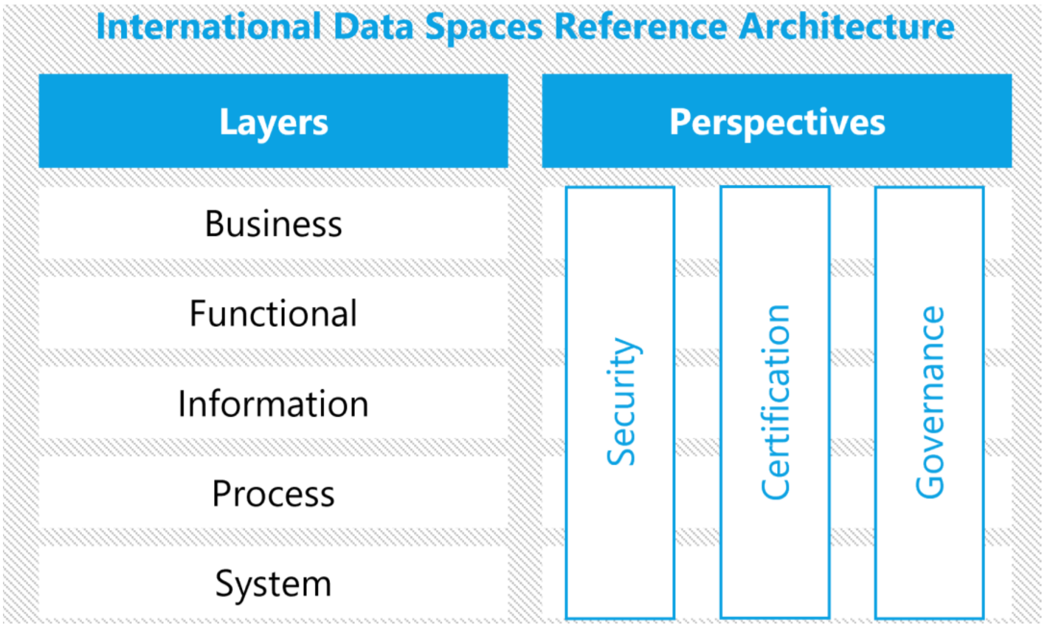

Figure 4-3: IDS RAM4.0 General Structure

FIWARE defined a Reference Architecture (**FIWARE for Industry**) [24] compliant with existing industry architectures which are capable of transforming the industrial sector into a networked, data-driven environment. The model aims to standardize and support developments of open digital twin platforms paving the way to build "powered-by-FIWARE" solutions able to manage the digital twin representation of the real world and using NGSI as the main integration API for enabling the interoperability and the sovereignty of data.

The architecture is composed by several components to cover and support the entire data cycle, from the shop floor to a wide range of services that can be built on the top.

The FIWARE Context Broker acts as an enabler for the intra and inter-company communications, complemented by the FIWARE NGSI API to harmonize access to data published using many different data formats.

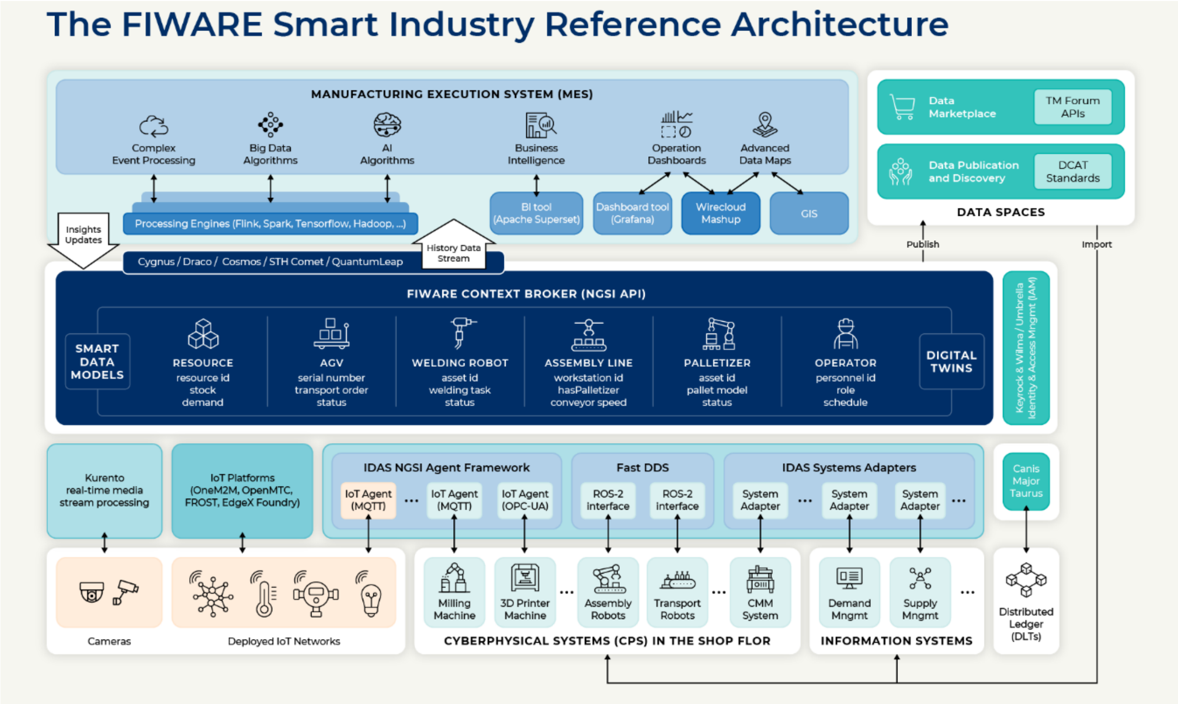

Figure 4-4: FIWARE Smart Industry Reference Architecture

4.2 Reference Architectures and Frameworks in Sister Projects

4.2.1 AI-based projects: AI REGIO

The AI REGIO Reference Architecture is defined starting from the analysis of relevant Reference Architectures for Industrial Internet of Things and I4MS past initiatives. It includes several aspects like the Artificial Intelligence integration, starting from the low layer where the data is processed and analyzed, to the higher level where AI supports the services, the Data Sovereignty Implementation, supporting data spaces where factories can access for exchange data in a trusted way with the scope of increasing the production quality and the supply chain improvements by the tools, platforms and services offered.

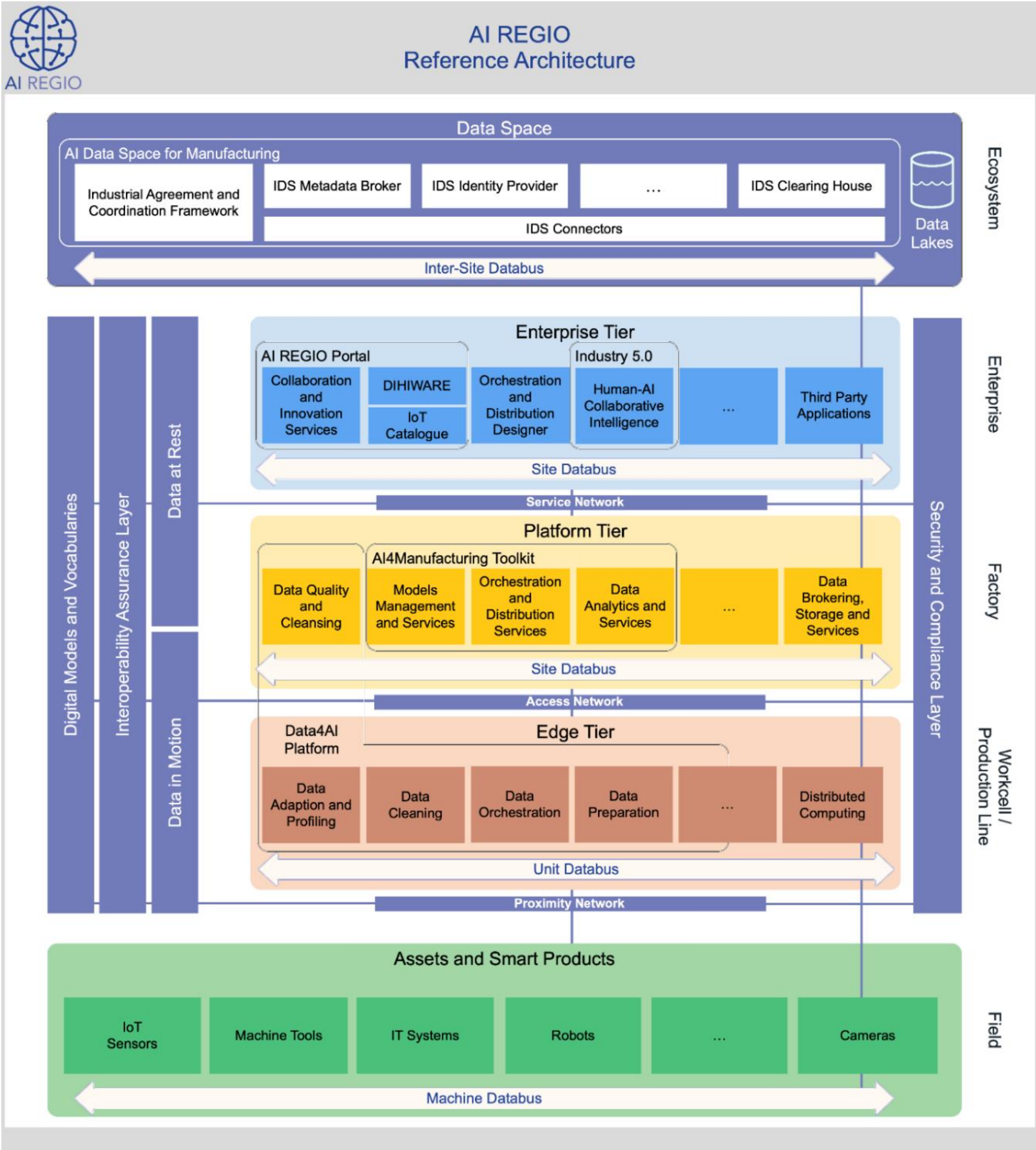

Figure 4-5: AI REGIO Reference Architecture

Below, a description to define the components represented in Figure 4-5:

- **Asset and Smart Products**: ecosystem of heterogeneous devices (IoT Sensors, Machine Tools, IT Systems, Robots, Cameras and so on) to gather machine data and make it available to the upper layers and IoT systems.
- **Edge Tier**: computes some data management and analysis functions, in small datasets, using data, applications, and services contained in the edge.
    - **Data Adaption and Profiling**: the service used for making the information available within its environment and adapt its execution accordingly.
    - **Data Cleaning**: the process able to guarantee the correctness of a huge amount of data, starting from data mining.

  - **Data Orchestration**: implements the logic for defining complex data flow processes between devices, data services, applications and people to produce desired outcomes.
  - **Data Preparation**: in charge of data manipulation to prepare it in the format needed to be analyzed.
  - **Distributed Computing**: is the link to the upper layer, allowing the data pipeline to communicate with the Platform services.
- **Platform Tier**: leverages the processing of data, enables making smarter, and sometimes faster, business decisions.
  - **Data Quality and Cleaning**: the process to discover and repair corrupted or inaccurate data, ensuring the quality of information in the dataset.
  - **Model Management and Services**: the services used to manage the models that feed the platform once the data have already been processed and ready to be used.
  - **Orchestration and Distribution Services**: services used to deploy the solution along the supply chain once it is designed thanks to the AI REGIO platform.
  - **Data Analytics and Services**: set of data analytics techniques and services used to take advantage from the information extracted/provided by the subsystems.
  - **Data Brokering, Storage and Services**: interact with the lower layer to gather data and storage it in order to make it available for the services in the platform.
- **Enterprise Tier**: receives the data and integrates it with data from other systems, to perform analysis across business silos, carrying out industry domain-specific business applications, related decision support and business intelligence systems. This tier provides interfaces to human consumers.
  - **Collaboration and Innovation Services**: allow the connection and information exchange, changing the way in which it is provisioned in order to increase the value of the service offered.
  - **DIHIWARE**: an integrated solution aiming to provide access to the latest knowledge, expertise and technology during SMEs Digital Transformation pathways toward piloting, testing and experimenting new digital technologies.
  - **IoT Catalogue**: a catalogue of solutions already for which there is a description identifying the specific problems solved.
  - **Orchestration and Distribution Designer**: is the service used to design the solution along the supply chain.
  - **Human-AI Collaborative Intelligence**: referred to Industry 5.0, it is the service offered to improve the interaction human-machine with the help of AI.

    - **Third Party Applications**: any other kind of application can integrate AI REGIO Platform.
- **Data Space**
    - **Industrial Agreement and Coordination Framework**: provides guidance to satisfy requirements in order to obtain a certification, including business, organizational and operational agreement.
    - **IDS Metadata Broker**: is an intermediary that stores and manages information about the data sources available in the data space.
    - **IDS Identity Provider**: offers a service to create, maintain, manage, monitor, and validate identity information of and for participants in the data space.
    - **IDS Connectors**: is the technical component to standardize data exchange between participants in the data space.
    - **IDS Clearing House**: is an intermediary that provides clearing and settlement services for all financial and data exchange transactions.
    - **Digital Models and Vocabularies**: the set of models and vocabularies used in all among layers allowing the interoperability.
    - **Interoperability Assurance Level**: ensures interoperability among all the levels finding a link to connect them, allowing the exchange of information.
- **Data in Motion**: real time data, typically represents Industrial IoT data coming from sensors and devices.
- **Data at Rest**: historical data, typically stored in IT and legacy systems.
- **Security and compliance Level**: service offered to all the layers, acts to ensure a trusted environment at all the levels.

4.2.2 AI-based projects: CAPRI

The CAP Reference Architecture is able to cover several industrial scenarios, from the edge to the cloud processing, passing through the Big Data analytics. It can support the analysis of streaming and batch data acquired from heterogeneous external sources with the support of machine learning technologies. In particular, a typical scenario in the IoT and industrial field is to react to events in real time based on the knowledge of past events, an essential information for predicting future behaviour, for example in order to identify any anomalies. In that sense, the platform integrates cognitive computing services to learn from experience and derive insights to unlock the value of big data.

The resulting three-tier RA is depicted in Figure 4-6 and defines several functional macro-components:

- **Smart Field** represents the physical layer and contains industrial devices, machines, actuators, sensors, wearable devices, robots, etc. that are spread in the shop floor, and supports the most common industrial and, more in general, IoT protocols such as OPC UA, MQTT, etc. Standards interfaces and protocols must be used, in order to represent the information collected from the plant and to connect and integrate actuators for implementing the sensing and control mechanisms. Data will be collected typically as Data in Motion (DiM) since data coming from IIoT systems are dynamic and should be ingested and processed in real time.

- **External Systems** component contains all internal and IT systems for supporting industrial processes (ERPs, PLMs, Supply Chain Management, customized, etc.). It represents static information that comes from Legacy Systems and can be collected as Data at Rest (DaR). Custom interfaces and system wrappers are a crucial part of the component, aiming to share data using smart data models for representing information.
- **Smart Data Management and Integration** is the core of the architecture since it contains the brokering, the storage and the data processing capabilities, including cognitive process analytics and simulation systems. Data in Motion (DiM), Data at Rest (DaR) and Situational Data are represented using standard information models and are made available using standard APIs. Thought the service layer, data can be collected and persisted supporting a wide range of databases (i.e., relational, nosql, time-series).
- **Data Ingestion** provides a bridge between the physical layer and the data brokering, where the data from the devices are shared in a standardized structure with the broker, putting the information at the disposal of the tools will analyse them. FIWARE IDAS Agent Generic Enabler is the IoT component that translates IoT-specific protocols into the NGSI-LD context information protocol, which is the FIWARE standard data exchange model. IoT Agent for OPC UA, IoT Agent for JSON, IoT Agent for Ultralight are some IDAS Agents in FIWARE Catalogue.
- The **Data Brokering** role is to manage the persistence and processing phases, where the main actors are the Orion-LD Context Broker, able to manage the entire lifecycle of context information including updates, queries, registrations, and subscriptions and Apache Kafka for high-performance data pipelines, streaming analytics, data integration, and mission-critical applications.
- The **Data Persistence and Processing** is composed of various FIWARE (Cygnus, Quantum Leap. Draco, Cosmos) and Apache (Livy, Spark, StreamPipes, Hadoop) components and is devoted to storing the data collected and process them. Cygnus, Quantum Leap and Draco are in charge to support the data storage (and pre-processing) acting as a data sink for the persistence vertical. Cosmos is oriented to big data analysis of Streaming and Batch processing over context data, while Spark is a parallel processing framework for running largescale, both batch and real-time, data analytics applications across clustered computers. Data flows can be defined with Draco running Spark jobs through Apache Livy. StreamPipes is an Industrial IoT toolbox to enable non-technical users to connect, analyse, and explore IoT data streams. Its runtime layer supports the addition of pipeline elements through a built-in SDK in the form of microservices.
- The **Data Visualization** gives a clear understanding of resulting data giving it visual context through maps or graphs. There are specific components, compliant with the most data source that fit different scenarios: Wirecloud enable the quick creation of

web applications and dashboards/cockpits, while Grafana supports the analytics and interactive visualization, more oriented to complex monitoring dashboards. Knowage offers complete set of tools for analytics, paying attention in particular at the data visualization for the most common data sources and big data, covering different topics like Smart Intelligence, Enterprise Reporting, Location Intelligence, Performance Management, Predictive Analysis. Finally, Apache Superset is fast, lightweight, intuitive, and loaded with options that make it easy for users of all skill sets to explore and visualize their data, from simple line charts to highly detailed geospatial charts.

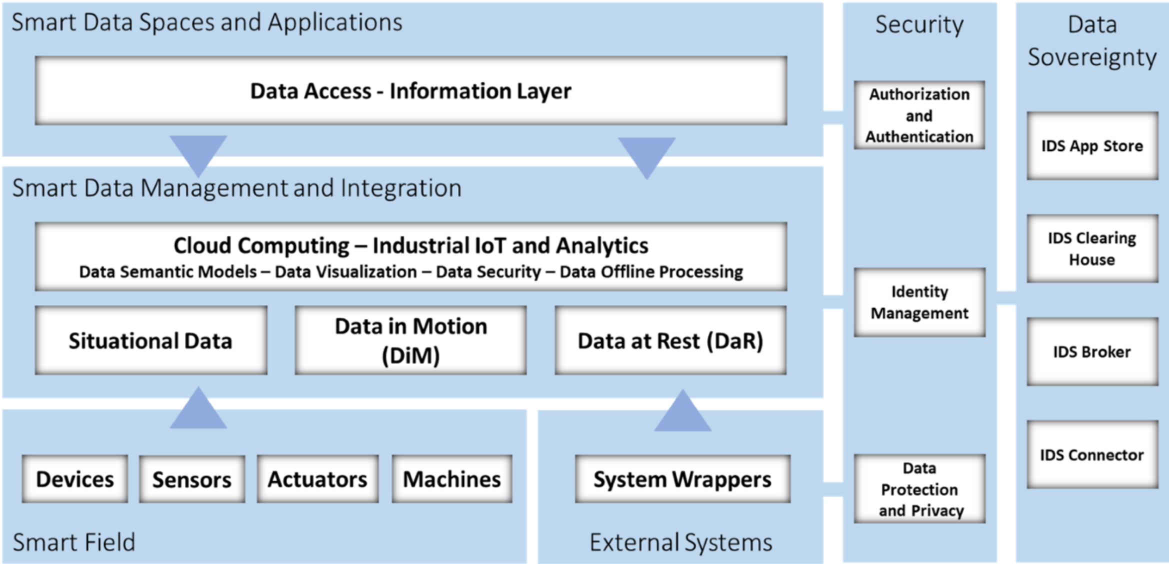

Figure 4-6: CAP Reference Architecture

The described architecture has been conceived with modularity as a main principle. Components in every layer can be combined according with a Lego-like approach, fulfilling the exposed data schema, making the architecture flexible and adaptable to the specific needs of the various application domains in process industry. At the same time the modularity makes possible to approach a microservices design of the application that produces smaller software code, to be organized as docker containers, so they could be run on smaller processing elements and restricted resources, as occurs in current plants, thus making easier the reuse of existing computing equipment. In this respect, the CAP Reference Architecture allows the implementation on both cloud and edge, that can be run on virtualized computing resources nearer to where multiple streams of data are created, thus addressing system latency, privacy, cost and resiliency challenges that a pure cloud computing approach cannot address and make a big difference in process industry. The edge implementation smoothly integrates with the cloud version, to enable data collection, storing, processing and presentation directly from the plant. Most of the short-term processing, including some data analytics, artificial intelligence and cognitive tasks could be managed at the edge, while cloud resources can be devoted to non-mission critical massive processing of data.

4.2.3 AI-based projects: KITT4SME

The KITT4SME Project aims to offer affordable, tailor-made AI solutions to small and medium-sized enterprises (SMEs) through a marketplace and adoption support network. The KITT4SME platform is a service mesh, multi-tenant, cloud architecture that assembles AI components from a marketplace to provide a tailor-made service offering for factories. The platform relies on a dedicated cluster software infrastructure that orchestrates the deployment and operation of services.

The KITT4SME platform services use Web interfaces with REST architectural style and agree on data formats, semantics, and communication mechanisms to perform workflow tasks. The platform adopts open communication and data standards to ensure service interoperability, allowing platform services to process data uniformly. The KITT4SME platform mesh uses intermediaries to route service traffic, secure communication, monitor service operation, and improve performance and availability. This infrastructure is independent of the platform services, allowing service developers to focus on service-specific features. Kubernetes and Istio are among the technologies considered to support the platform's modularity.

The service software is packaged with operating system images, which are run in the cluster using operating-system level virtualization. Each service can be deployed independently through an automated release process triggered by publishing images and deployment instructions in an online repository. Services are developed independently using various technology stacks, but most provide their functionality through REST APIs.

The software infrastructure has been designed to support the DIAGNOSE-COMPOSE-SENSE-INTERVENE workflow, which stands at the core of the KITT4SME philosophy. The platform allows the integration of different AI components into *kits*, through the platform marketplace (i.e., RAMP). Kits result from the DIAGNOSE procedure, which is devoted to discovering SMEs needs. Each kit corresponds to a set of deployment descriptors to deploy the components on the cloud instance running the FIWARE service mesh. The AI components are then fed by the SENSE phase, where a range of IoT devices and cyber-physical systems are connected to the platform. The platform provides a communication backbone for data to flow from the shop floor to the AI components, but also back again to issue commands to control devices or suggest corrective actions (INTERVENE).

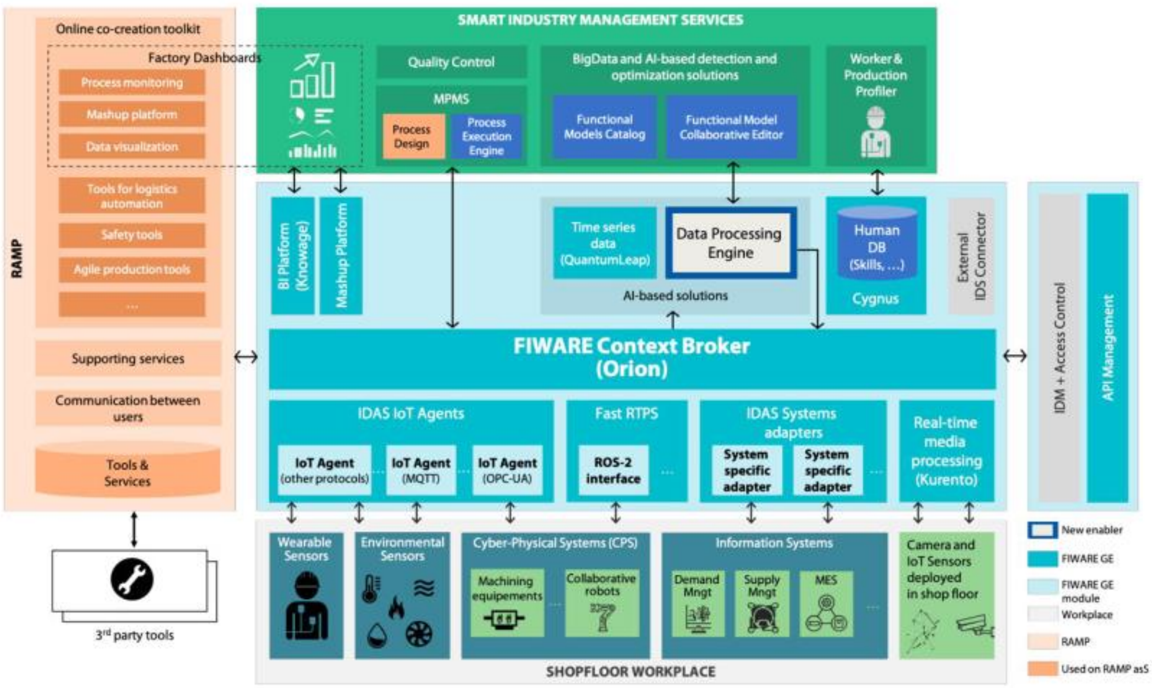

Figure 4-7: KITT4SME platform high-level architecture

The KITT4SME architecture supporting the DIAGNOSE-COMPOSE-SENSE-INTERVENE workflow is depicted in Figure 4-7. Starting from the lowest layer, the architecture covers data gathering from different devices deployed in the factory, feeding the knowledge base of the system with raw and pre-processed data:

- **Wearable sensors**, usually to monitor psychophysical parameters of workers, mainly related to their health and well-being.
- **Cyber-Physical Systems** typically involved within the process (e.g., machining equipment, collaborative robots).
- **Environmental sensors** to gather contextual information (e.g., air pollution, room temperature).

The next layer provides a set of interfaces for gathering additional context information, or triggering actuations:

- **IDAS Generic Enabler** offering IoT Agents meant to interface devices using common IoT protocols (e.g., LWM2M over CoaP, JSON over MQTT, OPC-UA).
- **FAST RTPS Generic Enabler**, which adopts ROS2 middleware and helps to interface with robotics systems.
- **Kurento**, to support the real-time processing of media streams and the incorporation of advanced application functions (e.g., augmented reality).

The next upper layer contains the data broker, i.e., **FIWARE Orion Context Broker**, which enables the management of context information in a decentralized and large-scale way. FIWARE provides its own Generic Enabler to persist Time Series historical data

(**QuantumLeap**), but data can also be streamed to third-party databases and distributed processing engines for analysis on historic data context.

Next, the KITT4SME architecture includes Big Data and AI-based detection and optimization tools components that process context history data to detect patterns and correlations, anomalies, malfunctions, unexpected behaviours, and outliers. The results of their processing are injected back into the FIWARE Orion Context Broker to activate the decision-making processes and actuations. These tools can be continuously created and edited using integrated functional model editors and added as new FIWARE components to the Functional Model Catalogue available to the open-source community. At the same layer, the KITT4SME architecture foresees four further components:

- **Human description Database**, which persists data related to the physiological parameters, information about workers, machine parameters and environmental data that contribute to create a complete representation of the worker in activity at the shop floor.
- The BI platform and suite **Knowage**: a FIWARE Generic Enabler to perform traditional business analytics over classical data sources, databases and big data systems.
- A **Mashup Platform** as KPI-driven process governance dashboard: it helps the different operators within the factory to access the relevant context information representing the latest status of the processes.
- **External IDS Connector**: a component of the IDSA reference architecture that serves as a trustful interface between internal data sources and external data consumers, enabling secure and interoperable data exchange.

The results from the Big Data and AI-based detections and optimization tools activate decision-making mechanisms, mainly managed by the MPMS. The decision-making process includes user interaction and behavioural updates for involved CPS to optimize process performance and worker well-being. Interventions are launched at different levels and orchestrated to support operators and improve performance.

Finally, the KITT4SME Project exploits RAMP to provisioning various components through Software-as-a-Service, allowing for direct use of FIWARE-compatible equipment (robots, machines, sensors, mobile devices etc.) in the production floor without the need for software deployments or IT expertise. The KITT4SME platform is supported by an IDM Generic Enabler that provides secure and private authentication, user profile management, privacy-preserving personal data disposition, Single Sign-On (SSO), and Identity Federation across multiple administration domains.

4.2.4 AI-based projects: COGNITWIN

The goal of the COGNITWIN Project was to enhance the potential of the process industry in Europe by creating and validating a new approach for cognitive digital twins affordable for all process industries. The COGNITWIN Project decided to use the Asset Administration Shell (AAS) specification to realize digital twins (DTs), because it provides a standardized model as well as standardized interfaces.

A DT is the digital representation of an asset. It comprises relevant information from sensors attached to the asset as well as from relevant external sensors. To enable interoperability within and across factories, DTs should implement a common and standardized application programming interface (API). Current existing DT standards typically represent a DT as a set of properties, services and events and provides a HTTP/REST-based API to interact with the DT. This is reflected in Figure 4-8 in the upper right part of the DT and by the user/application that is using the DT API [25].

A DT may also comprise a set of models. These models can be of different types, e.g., physical or data-driven, e.g., AI models. In the COGNITWIN Project has been found that all models have in common, that they take the changing values of properties of the DT as input, apply some logic and report back their result to the DT by either updating existing properties or creating new ones[21]. As models represent a logic processing step they need to be executed. For each type of model, this requires a model execution environment that can be deployed inside and/or outside of a DT. The decision where to deploy the execution environments is a trade-off between the ability of the DT to run as stand-alone application and the resource requirements, especially because using external model execution environments can be shared between multiple DTs.

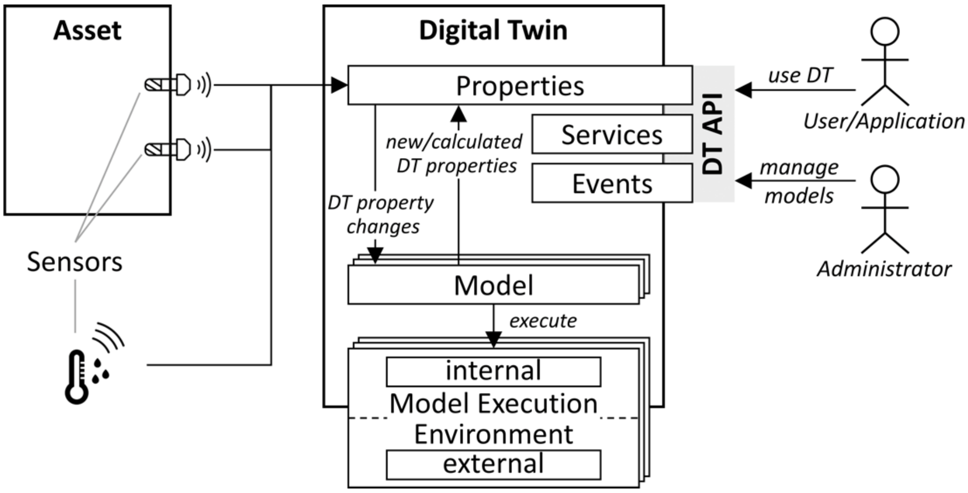

Figure 4-8: General architecture for realizing Hybrid Digital Twins

In Figure 4-8, models are defined as a set of instructions that operate on and produce (new) properties of a DT on a technology-agnostic level that can be executed in a model execution environment. To implement this, a concrete technology to define and execute such models has to be chosen. For this purpose, the COGNITWIN Project used Apache StreamPipes[22]. Figure 4-9 shows how this choice influences the architecture. As StreamPipes is a stream processing framework, models are realized using the pipeline concept. As model execution environment an external StreamPipes deployment was used. It also provides an easy-to-use visual editor for creating and managing pipelines. As StreamPipes is a generic tool for creating processing pipelines using many different kinds of data sources and sinks, e.g., different network protocols, files, or databases, custom adapters for AAS-based DTs called

[21] https://www.sintef.no/globalassets/project/cognitwin/public-reports/d4.2.pdf
[22] https://streampipes.apache.org/

DT Source and DT Sink have been created. For more information on integration between DTs and ML/AI services using StreamPipes, see [25].

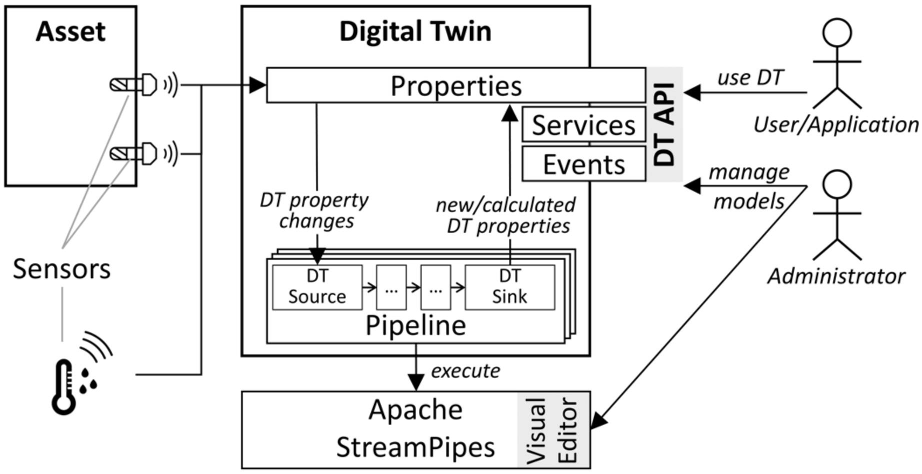

Figure 4-9: COGNITWIN solution for integration between DTs and AI/ML models

To implement this architecture, the Fraunhofer Advanced AAS Tools for Digital Twins (FA³ST) was developed. FA³ST Service is an open-source Java-based software for creating and managing digital twins (DTs), so-called Asset Administration Shells (AASs). It is based on the standard document(s) published by the Platform Industrie 4.0 and was used in the COGNITWIN Project to develop standard-conform executable DTs in the pilots. Main features are that it is designed to be easy to use and extend and that it can be connected to assets using arbitrary communication protocols. To create a reactive DT, FA³ST Service should be started with an AAS model and a configuration file. The result will be a DT with an AAS-compliant DT API for interaction of the DT with the outside world that can synchronize itself with the underlying asset(s). More information on FA³ST can be found in [26].

For the use and integration of DTs across company borders, the COGNITWIN Project proposed to integrate DTs with the IDS to ensure security and confidentially of exchanged information. Figure 4-10 shows a conceptual integration of DT into IDS. From inside the company that owns/hosts the DT (i.e., Company A), an actor, which can be either human but typically is an application, can interact directly with a DT via the DT API. Actors from outside the company, i.e., from Company B, will have to use the IDS API to interact with the DT. This requires both Company A and B to provide a (properly configured) IDS connector component. Additionally, if the actor wanting to interact with the DT across company boundaries is an application, it needs to be certified to be «IDS ready». More information can be found in [27].

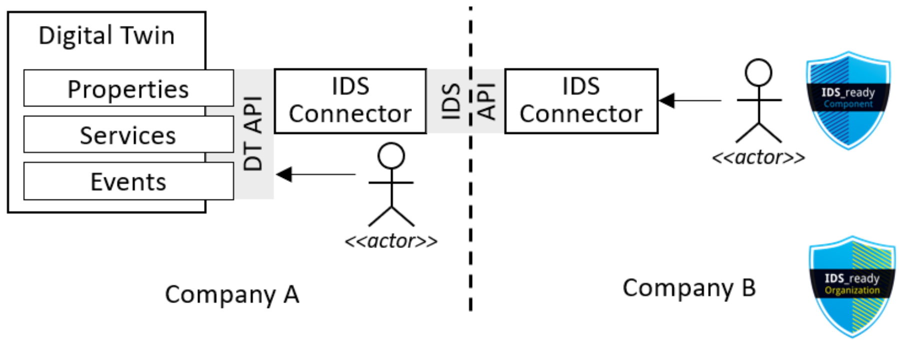

Figure 4-10: DT integration with IDS

4.2.5 Connected Factories and ICT-07 Cluster Projects

Regarding the manufacturing domain, Connected Factories and ICT-07 Cluster Project have to be mentioned. During the Project Connected Factories, especially in Connected Factories 2, POLIMI has developed, in collaboration with VTT, the so called "Circular Economy Pathway". This pathway aims at providing a guiding tool to manufacturing companies towards the embracement of circular manufacturing strategies (e.g., remanufacturing, recycling, industrial symbiosis, etc.). Indeed, through this pathway, companies can understand where they are currently positioned, thus at which maturity level they are located based on the analysis of their internal processes and of their relationships with external stakeholders.

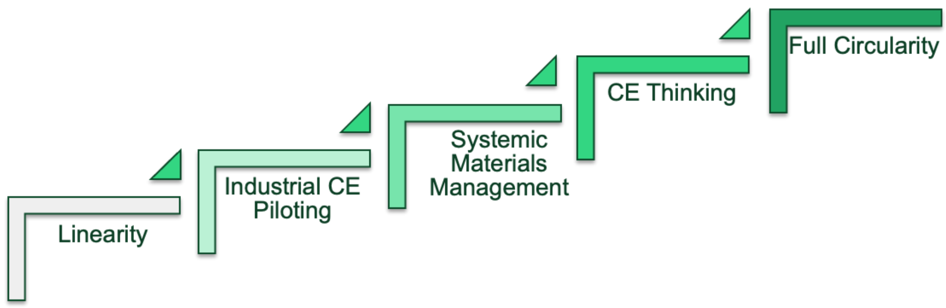

Figure 4-11: Maturity scale [28]

Starting from the linear level according to which only mandatory rules are followed, it is possible to achieve gradually the fifth level, the highest one, according to which resource optimization happens thanks to the internal re-design of processes and products but also thanks to the establishment of specific relationships with other stakeholders enabling the recirculation of resources.

The analysis is performed across the 5 levels of maturity covering the traditional value chain taking as reference the one developed by SITRA (The Finnish Innovation Fund), Technology Industries of Finland, and Accenture, Circular Economy Business Models for the Manufacturing Industry: Circular Economy Playbook for Finnish SMEs. [https://teknologiateollisuus.fi/fi/circular-economy-playbook.](https://teknologiateollisuus.fi/fi/circular-economy-playbook)

Figure 4-12: Traditional Value Chain SITRA [28]

This pathway is available on the EFFRA (European Factories of the Future (FoF) Research Association) portal.

Regarding the other projects, details are below reported.

4.2.5.1 DigiPrime

DigiPrime [29] platform is an IT system that enables digital data collection and data acquisition from the business actors of the circular chain, including for example manufacturers, demanufacturers, remanufacturers, recyclers, certification authorities and more. These data are stored in the platform and used to provide a range of value-added services to the various stakeholders. These services can be classified into two broad categories:

- **Operational Services**: These services are typically restricted to a specific sector and provide valuable insights into the operations of a particular business actor. For example, manufacturers can use the platform to collect data on the quality of raw materials, the efficiency of production processes, and the sustainability of their operations. Demanufacturers can use the platform to collect data on the types and quantities of materials that can be extracted from used products, and the efficiency of their processes. Recyclers can use the platform to collect data on the quality of recycled materials, the efficiency of recycling processes, and the environmental impact of their operations.

- **Value Chain Services**: These services are provided across the cross-sector value chain and provide a holistic view of the circular chain operations. For example, certification authorities can use the platform to collect data on the sustainability of the circular chain operations, including the environmental impact, social impact, and economic impact of the operations. Remanufacturers can use the platform to collect data on the quality of remanufactured products, the efficiency of remanufacturing processes, and the demand for remanufactured products. The platform can also provide insights into the demand for recycled materials and the availability of raw materials, enabling stakeholders to optimize their operations and minimize waste.

The platform enables the different stakeholders to access the outputs of these value-added services. The operation of the platform is empowered by:

- Identify Management Services that enable users' secure access to the services of the platform.

- Data Collection services that manage data acquisitions from the various data sources.

- Data Sharing functionalities at two complementary levels, namely local level (i.e., within a given sector) and global level (i.e., across sectors). Local level actors form local federations, while cross-sector interactions of business actors take place at higher level federations (i.e., global federations).

- Ledger Services that make use of distributed ledger technology (i.e., blockchain) to provide data provenance functionalities.

Figure 4-13 below illustrates the main components of the DigiPrime platform for cross-sectorial CE collaborative networks.

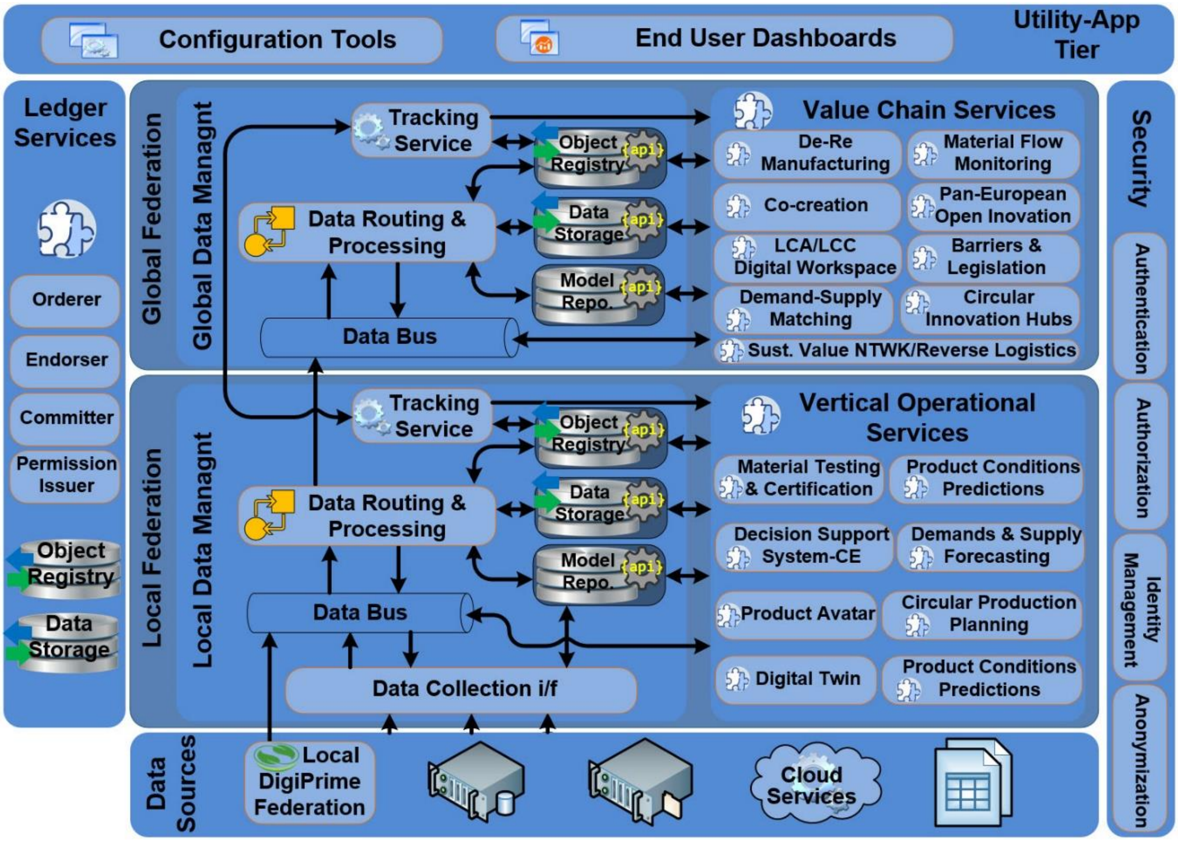

Figure 4-13: Logical Architecture of the DigiPrime Platform

The overall design of the platform has considered guidelines and best practices from reference architecture models for industrial applications, namely reference architecture models for industrial systems and for industrial data spaces. As shown in Figure 4-13 above DigiPrime's core building blocks are:

- **Identity Management Services**: The DigiPrime platform comprises authentication and authorization services, which are applicable to both local and global federations of DigiPrime. They include (i) Authentication: Authentication of the various users of the DigiPrime digital platform. (ii) Authorization: Provides stakeholders with access to the capabilities of the platform in-line with their roles in the circular chain; (iii) Identity Management: a set of framework services and policies that manage users' authorizations within the digital platform. It manages multiple authorizations and authentications in heterogeneous environments (e.g., credentials like certificates and single sign on functionalities).

- **Data Sources and Data Collection**: The digital platform is a data-driven system, which facilitates the structured exchange of data across different CE stakeholders.

Hence, different data sources can be integrated in the platform to collect information about products, materials, recycling processes and more. Data sources are naturally integrated within a local federation. It is assumed that individual data sources are not provided as direct inputs to a global federation. This is because global federations comprise data provided by two or more local federations rather than individual data sources. Local and global federations constitute loosely connected service components that facilitates late binding, either by manual configuration or through service orchestration.

- **Local and Global Federations** which combination provides a two-level approach to supporting data exchange. The distinction between global and local federation is primarily logical. From an implementation perspective, local and global federations share data using similar technological infrastructures. In more detail:
    - A **local federation** enables the exchange of data and services interactions between stakeholders within a specific sector or business domain. In support of a local federation, the DigiPrime architecture specifies the following services: (i) Data Storage: Hold data about the circular economy processes and their support by DigiPrime. (ii) Models Repository: Hold various models that will be specific to the DigiPrime services, such as Product Condition Prediction and Lifecycle assessment models and potentially models for specific services of the DigiPrime digital platform. (iii) Operational Services: Enables data sharing and service interactions across the Operational Services of the DigiPrime digital platform.
    - A **global federation** of the architecture enables cross-sector data sharing and service interactions, i.e., sharing of data and invocation of services across two or more local federations. The global federation sub-system includes the same services as the local federation. Specifically: (i) Data Bus: enables seamless and effective data transfer across all components of the global federation. (ii) Data Routing and Processing: enables pre-processing and routing of data streams to the various components of the global federation. (iii) Tracking Service: provides tracking of objects and processes at the level of the global federation. (iv) Object Registry: contains information about physical objects (components, materials, products) at the level of the global federation. (v) Data Storage: a set of data repositories and data services that enable the management and exchange of data at the level of the global federation. (vi) Models Repository: manages models used by services of the global federation. (vii) Value Chain Services: the global federation subsystem that enables data sharing and service interactions across the Value Chain Services of the platform.
- **Operational Services and Value Chain Services**: On top of the Data repositories and the data management services, the Operational and Value chain services are implemented.
- **Ledger Services**: which support decentralized and trusted sharing of data. Specifically, the platform exploits the security, decentralized trust and anti-tampering properties of DLT to support: (i) Data provenance and traceability through recording

metadata about each CRUD (Create Update Delete) data operation. (ii) Decentralized consensus on the applicable data policies to ensure that a data policy is agreed among the participants rather than being enforced by a trusted third party.

4.2.5.2 KYKLOS

KYKLOS 4.0 platform aims at providing circular manufacturing capabilities in the form of software, hardware and methodological services to support the circular manufacturing whole process, from the design of the product until the testing and packaging of it.

Figure 4-14 below shows six main activities within the circular manufacturing process and how the KYKLOS 4.0 platform supports each of them.

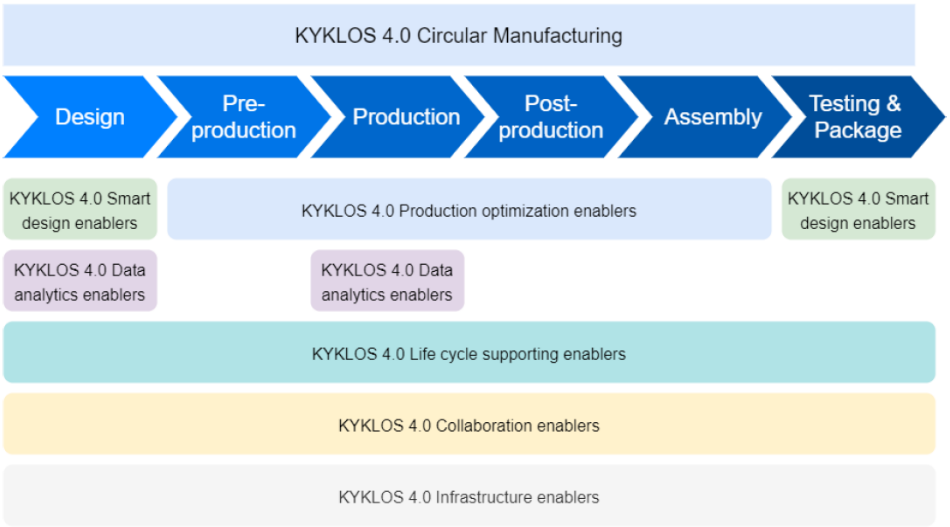

Figure 4-14: KYKLOS Circular Economy Process

There are seven types of enablers or components in the KYKLOS 4.0 platform:

- **KYKLOS 4.0 Smart design enablers** include KYKLOS 4.0 components that support the design of the customized product in terms of best materials selection, best specification sizes and orientation or simulation of the final product. They are not involved only in the design step, but they get feedback at the testing phase of the manufacturing process in order to learn and improve their functionality.
- **KYKLOS 4.0 Production optimization enablers** contain KYKLOS 4.0 components that support on the production phase, including preparation of the production, the production phase itself, post-production and assembly. KYKLOS 4.0 components support this phase by monitoring in real-time the production as well as providing simulation of the process in case some of the inputs change. KYKLOS 4.0 components also provide a decision support system (DSS) based on the indicators calculated during the production phase in order to enhance both the production and the circular indicators. Moreover, KYKLOS 4.0 components offer innovative technologies such as Augmented Reality (AR) for improving the guidance and support of the process to the operators.
- **KYKLOS 4.0 Data analytics enablers** include KYKLOS 4.0 components that support the aforementioned enablers (i.e., KYKLOS 4.0 Smart design enablers and

KYKLOS 4.0 Production optimization enablers) by providing Artificial Intelligence (AI) -based services. These services are used for (i) improving the additive manufacturing (AM) design and (ii) performing predictions concerning maintenance operations.

- **KYKLOS 4.0 Life cycle supporting enablers** include KYKLOS 4.0 components that cover the whole life cycle of the circular manufacturing, by providing circular and sustainability related KPIs monitoring or performing a trustworthy tracking of the different parts of the final product in order to ensure that all parts comply with the user requirements.
- **KYKLOS 4.0 Collaboration enablers** include KYKLOS 4.0 components that promote the data sharing among different KYKLOS 4.0 components. They provide multiple services such as (i) an ISO 10303-242 standard compliant repository to support the manufacturing process, (ii) trustworthy auditing mechanisms to have automated quality inspections, and (iii) stream data processing platform and visual analytics handling heterogeneous types of data from multiples sources.
- **KYKLOS 4.0 Infrastructure enablers** include KYKLOS 4.0 components that support the rest of the KYKLOS 4.0 platform with the following services: common and shared repository that support heterogeneous data as well as an interoperability layer to gather all this data, common access point in form of Graphical User Interface (GUI) to the KYKLOS 4.0 ecosystem for the end users, and authentication and authorization services.
- **KYKLOS 4.0 Outreach enablers** include KYKLOS 4.0 components that promote the capabilities that the KYKLOS 4.0 platform can provide to the end user.

4.2.5.3 SHOP4CF

SHOP4CF (Smart Human Oriented Platform for Connected Factories) is an EU-funded Project within the eighth framework program Horizon 2020 that aims to create a unique infrastructure for the convenient deployment of human-centric industrial applications.

The Project is developing a comprehensive software platform containing a wide range of components that cover a broad spectrum of industrial requirements, especially in the context of modern, flexible, and data-rich manufacturing.

The overall vision of SHOP4CF is that tomorrow's production requires both machine skills (e.g., high accuracy, precision, or persistence) and human resources (e.g., creativity, adaptability, or tactile sense). Therefore, all components considered in the SHOP4CF software platform aim at the mutual complementation of human labour and machines in order to improve the working conditions by:

- Automating Monotonous / Laborious Work
- Increasing Human Productivity Through Smart Assistance

The SHOP4CF architecture is based on the Kruchten 4+1 framework, mainly on the logical view taking into consideration software, platform and data.

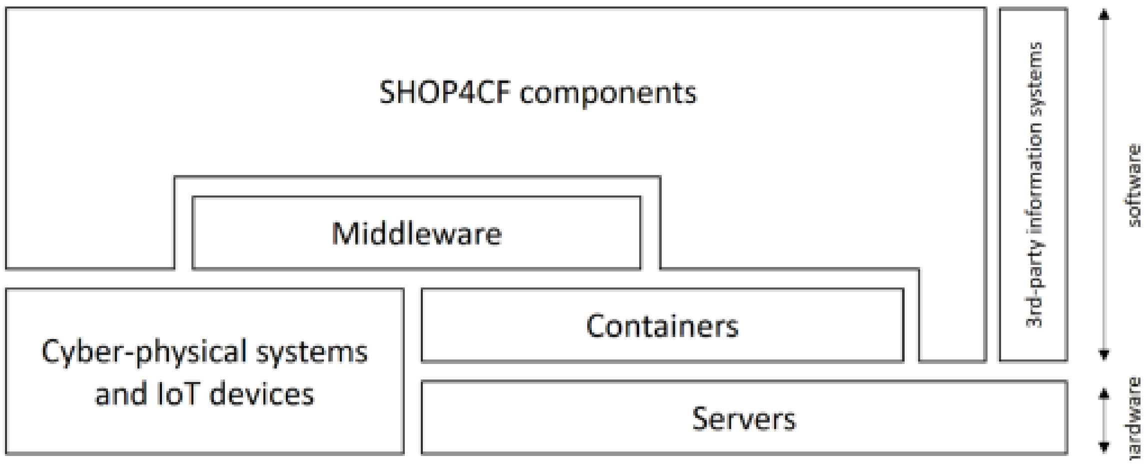

Figure 4-15: SHOP4CF: Top-level logical platform architecture

4.3 Inputs from Relevant Initiatives

4.3.1 [DAIRO]

The Big Data Value Association – BDVA, (from 2021, DAIRO – Data, AI and Robotics aisbl), is an industry-driven international not–for-profit organisation with more than 230 members all over Europe and a well-balanced composition of large, small, and medium-sized industries as well as research and user organizations.

The association aims to enable the digital transformation of the economy and society considering Artificial Intelligence and Data as key drivers in several areas such as Industrial AI, data platforms, data spaces, big data, standardization, etc.

DAIRO defined the Big Data Value (BDV) Reference Model with two main concerns:

- Horizontal concerns cover specific aspects along the data processing chain, starting with data collection and ingestion, and extending to data visualisation. It should be noted that the horizontal concerns do not imply a layered architecture. As an example, data visualisation may be applied directly to collected data (the data management aspect) without the need for data processing and analytics.
- Vertical concerns address cross-cutting issues, which may affect all the horizontal concerns. In addition, vertical concerns may also involve non-technical aspects.

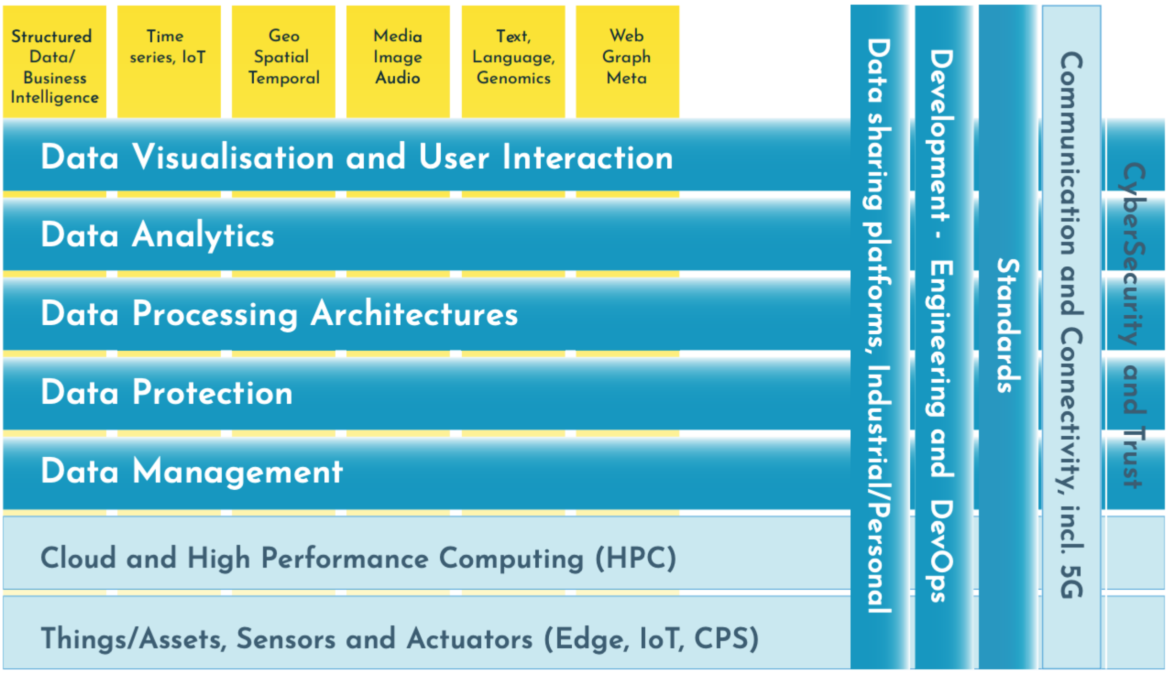

Figure 4-16: BDV Reference Model

4.3.2 AI4EU

The AI4EU Project was initiated in 2019 with the goal of constructing the first AI on-demand platform in Europe. This platform is based on four main pillars, which are **community**, **content**, **tools**, and **experiments**. The overarching objective is to foster a collaborative ecosystem that allows AI users to interact and gain access to various AI tools from multiple European AI projects and contributors.

The AI4EU on-demand platform is comprised of three main components:

- A web-based space for the European AI community to interact.
- A technical space in which AI modules are registered, referenced, and accessed through the experiment platform to build AI services.
- A testing space in which AI solutions can be deployed using state-of-the-art resource management.

While the first compartment is partially accessible without login to access AI4EU AI resources links, AI news, events, cafés, open calls, and public deliverables, the remaining part is private and requires European Login (European SSO). The remaining part is composed of the AI4EU Experiment platform, its AI catalog, and the AI.LAB Playground, which are the core of the collaborative ecosystem. On one hand, the experiment platform allows users to onboard new AI modules and publish them in the AI catalog, as well as create AI solutions from public modules in the catalog. On the other hand, the AI.LAB Playground allows users to easily deploy and test solutions in a pre-configured environment.

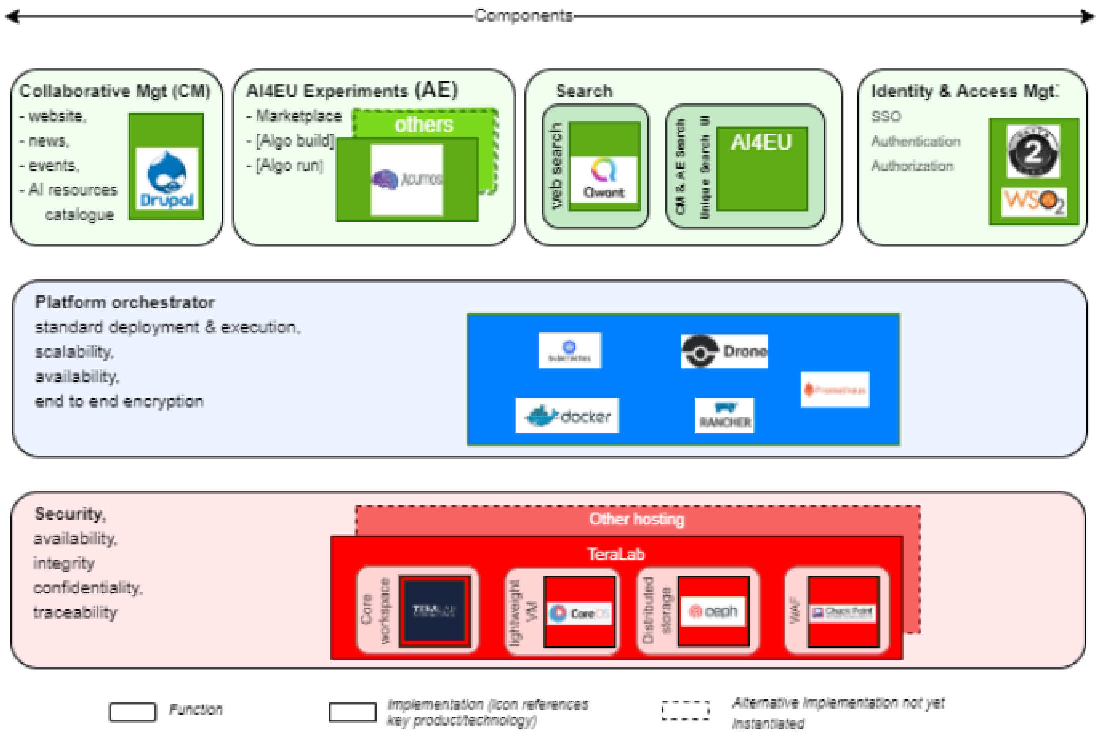

Figure 4-17: Reference Architecture of AI4EU

The architecture of the AI4EU platform is based on three layers: the End User Layer, the Orchestration Layer, and the Infrastructure Layer.

- **End User Layer**: comprehending all web applications and services providing functions and features for user interaction. This layer contains the following components:
  - **Collaborative Management (CM)** component, based on Drupal, implementing the "social network" feature of the platform that allows users to exchange information and collaborate.
  - **AI4EU Experiment Management (AEM)** component that integrates the ACUMOS open-source technology with other components and interoperates with the CM component through a two-way conversion from the AEM component catalogue and the CM one.
  - **Identity and Access Management (IAM)** that centralizes the authentication and authorization management.
  - **Search Component** that provides a front end to handle full scope queries and by delegating sub-queries to its sub-components. To ensure modularity, some components in the AI4EU platform access their own data in their own databases. However, if a shared database is required, it is treated as a module, such as the AI Resources Catalog, which is accessed from both the CM and AEM components using dedicated APIs.
- **Orchestration Layer**: this layer covers the availability, scalability, easy deployment and monitoring requirements of the platform regarding the end user components management, as well as applications useful for platform developers. An admin

endpoint is also designed to allow a privileged access to administrators to manage the platform.

- **Infrastructure Layer**: this layer provides the bare metal resources to the platform orchestrator (CPU, RAM, storage, network, GPUs) and covers both security and migration requirements.

The AEM component in AI4EU is implemented using ACUMOS, an open-source platform that enables users to build and deploy AI applications. It internally utilizes tools such as Tensorflow, scikit-learn and models that can connect with common APIs, allowing the deployment of AI solutions and models as microservices with Docker. Its reference architecture offers four primary functions:

- **Onboarding**: implemented through a web interface that enables users to load their resource assets onto the platform, linking with Docker registries.
- **Validation**: a component that verifies the validity of the AI module and the license provided during the onboarding process.
- **Portal Marketplace**: a component linked with the AI resource catalog allowing the publishing and retrieval of new AI assets.
- **Design Studio**: a no-code, drag and drop web interface to build, save, and validate AI solutions by composing AI modules and functional modules from the catalog.

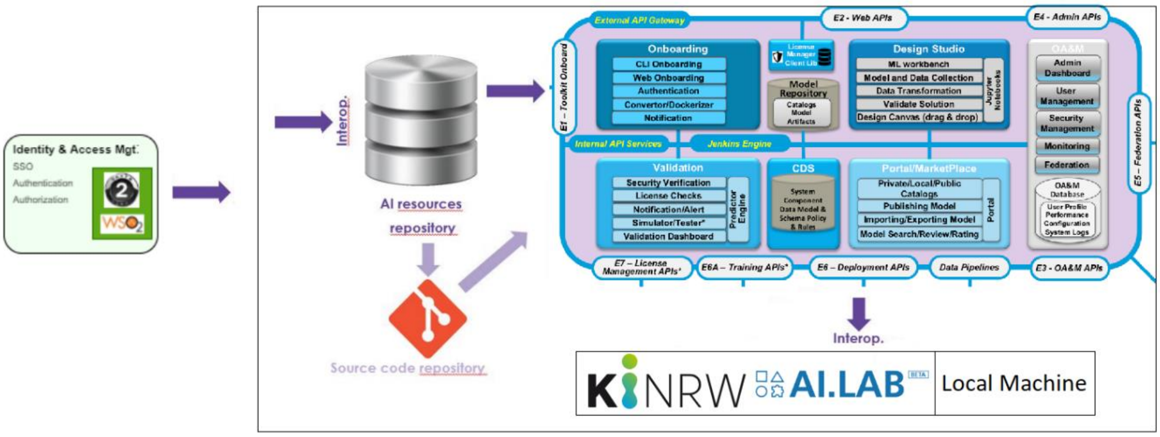

Figure 4-18: Zoom on ACUMOS and its interaction with other AI4EU Components

AI4EU utilizes the ACUMOS platform, accessible via HTTPS and European Login that implements the AI4EU IAM component, for building and deploying AI applications. ACUMOS can access the AI Resource Repository through API or Direct Access, showing them in its marketplace interface, and is hosted on the infrastructure layer, which provides a Kubernetes Cluster and all necessary computing resources. AI4EU offers an external tool, AI.LAB, for deploying AI solutions in the trial space compartment, or alternatively, they can be deployed on a local machine.

5 Circular TwAIn Reference Architecture

5.1 Design Principles

In order to design the Circular TwAIn Reference Architecture several concerns (apart the classic ones needed for implementing the digital transformation) have been considered:

- **Edge-cloud**: to support, on one hand cloud platforms, centralized with high processing and compute power and greatest storage capacity considering the existing standards and patterns (i.e., the three-tiers architecture pattern). On the other hand, the edge with decentralized, low latency and local processing features.
- **Artificial Intelligence**: the Project aims to support collaborative and explainable AI techniques, considering the design and the run time embracing the cloud and the edge deployments. The AI engine should be ingested by AI models trained with pre-processed data coming from the pilots.
- **Digital Twin**: three classes of Digital Twins should be described (product, process and human) and supported by the Reference Architecture, leveraging on the existing standards (i.e., ISO 23247-2).
- **Data Space**: data sovereignty should be supported from technical and business perspectives. Data Space components are aligned with the Design Principles position paper from the OPEN DEI CSA.
- **Circular Economy**: applications for implementing circularity should be supported and described. The list of defined applications is not exhaustive but is representative of the main pilot scenarios that will be validated in the Project.

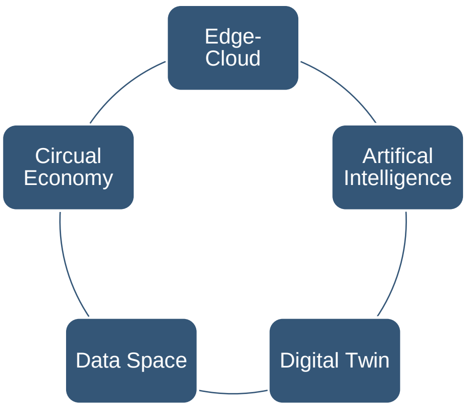

Figure 5-1: Circular TwAIn Reference Architecture Concerns

5.2 Circular TwAIn Reference Architecture

The Circular TwAIn Reference Architecture, which is based on the edge-cloud paradigm, has been designed to facilitate the development of circular applications, such as *recycling, re-manufacturing, de-manufacturing*, and more. It has been designed as a logical view, in order to emphasize the necessary components for supporting the three main pillars that should sustain the “project building”: circularity, data space and Artificial Intelligence. This architecture provides support for such applications through various means, including:

- Seamless data sharing between circular actors, which enables the efficient transfer of data among the stakeholders involved in the circular process.
- Collaborative and Explainable AI, which allows multiple stakeholders to work together on AI projects and provides them with the necessary tools to understand how the AI models are making decisions.
- Digital Twins (Product, Process, Human), which create a virtual representation of a product, process, or human, and allow stakeholders to experiment with different scenarios and optimize the circular process.

Cloud Layer - Human and Applications

- **Explanations:** XAI (eXplainable Artificial Intelligence) techniques have yielded insightful outcomes that allow humans to gain a deeper understanding of AI models and their behavior within pipelines. These findings are readily available to individuals seeking to enhance their knowledge of the intricate workings of AI, thus empowering them with valuable insights into the behavior of such models.
- **Assistance and Interaction:** combination of outputs from AI models that have been enhanced with explainability methods to enrich human cognition and experience by providing valuable insights within interactive environments.
- **Parametrization, Labeling, Training:** application that offers the possibility for the user to create datasets from raw and unstructured data by employing dedicated tools and algorithms for data pre-processing, cleansing, and transformation. In addition, the user can develop AI models and pipelines from scratch, configuring and tuning their settings and parameters according to their specific needs and use cases. Moreover, the platform enables users to provide feedback in the form of annotations, labeling, or other techniques, to improve the quality and accuracy of the models and pipelines during the training phase.
- **Other possible applications:** comprehensive support for a diverse range of requirements and applications, including Digital Twins and XAI-based applications, among others.

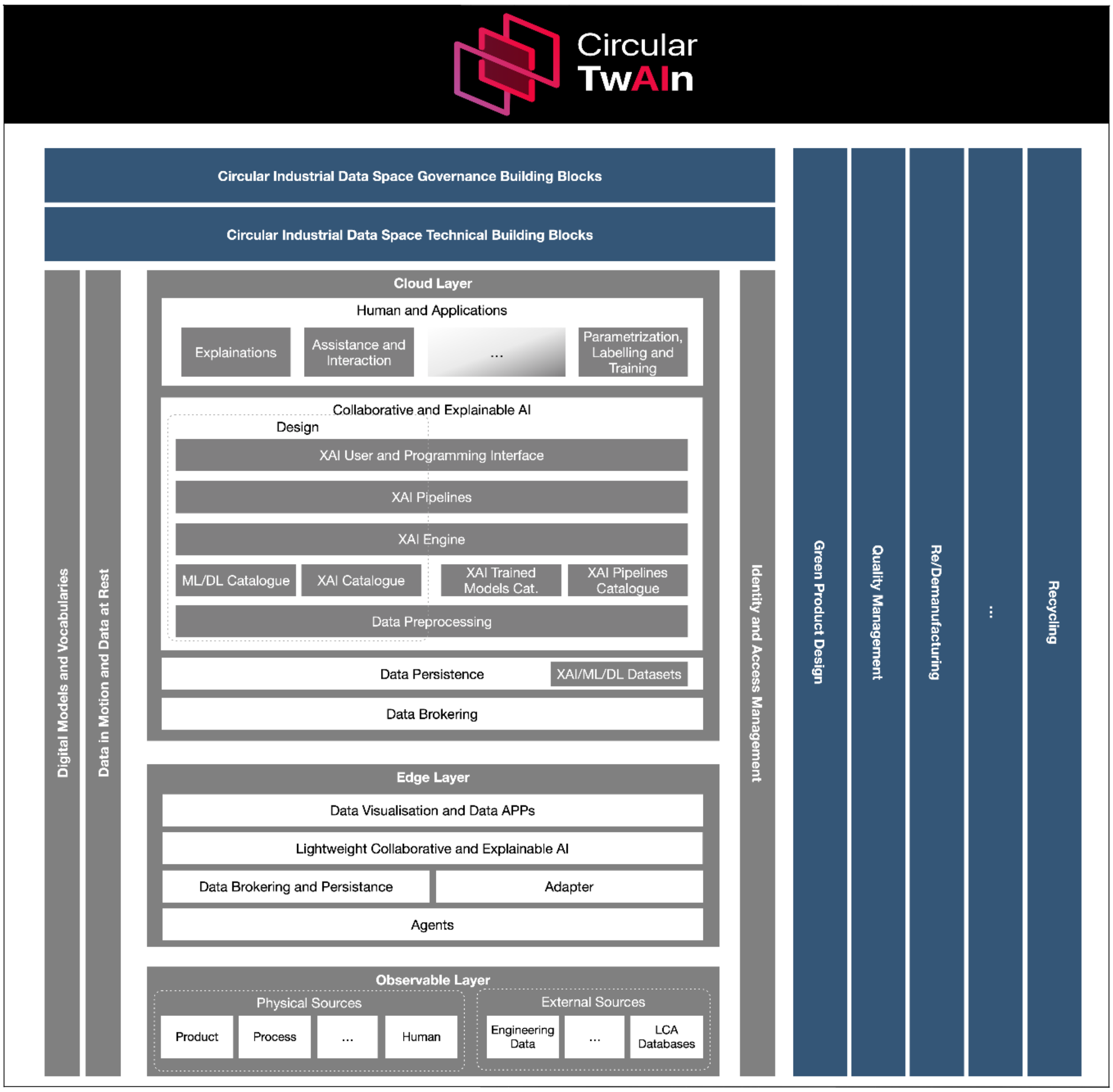

Figure 5-2: Circular TwAIn Reference Architecture

Cloud Layer - Collaborative and Explainable AI

- **XAI User and Programming Interface:** this layer is designed to offer users a comprehensive set of tools for both data/results/explanation dashboarding and XAI programming interfaces. The first set of tools enables users to visualize and interact with model results and behavior from the operator's perspective, thus facilitating a better understanding of the underlying AI model. The second set of tools provides interfaces (either at the notebook level, such as programming, or at the visual level) for building datasets, customizing AI assets for training, and constructing XAI pipelines.
- **XAI Pipelines:** the fundamental building blocks of Collaborative and Explainable AI, they are the core "assets" that arise from the integration of reusable AI and XAI components. These can be created from the ground up by assembling various pieces using either notebook or visual interfaces and can subsequently be executed.

- **XAI Engine:** the XAI Engine comprises a set of sophisticated tools that enable the design and execution of XAI pipelines and models. It provides access to all relevant catalogues, acting as an experimental and design platform for the operational production of XAI for the DTs. Additionally, it orchestrates data flow between the input and the different AI/XAI modules of the pipeline, before collecting and rendering the results in an easily accessible format.
- **ML/DL Catalogue:** a catalogue populated with state-of-the-art machine learning and deep learning algorithms is a vast collection of libraries that are highly valuable and instrumental in building artificial intelligence models from scratch. The collection comprises an extensive range of algorithms that are meticulously curated and continuously updated to stay abreast with the latest advancements in the field of AI. This resourceful catalogue empowers developers to leverage cutting-edge algorithms to create AI models that are customized to cater to the unique requirements of their specific use cases.
- **XAI Catalogue:** a comprehensive catalogue of cutting-edge eXplainable Artificial Intelligence (XAI) techniques is made available to users, allowing them to match these techniques with their AI models, thereby creating XAI models. These XAI techniques provide users with advanced and effective methods of explaining their AI models.
- **XAI Trained models Catalogue:** a comprehensive list of domain-specific AI models that have been trained, explained, and assessed for their reliability and effectiveness, which can be used as a basis for building XAI pipelines.
- **XAI Pipelines Catalogue:** a list of XAI applications (pipelines) that have been specifically developed for a particular domain. Each application comes with an explanation technique that enhances the transparency and interpretability of the model's decision-making process. The applications can be easily and quickly deployed and scaled for practical use.
- **Data Preprocessing:** a set of advanced tools and modules for data preprocessing that enable the creation of high-quality datasets from raw data. These datasets are then made ready to be ingested by the XAI Engine, or to simply apply preprocessing techniques to incoming data. This ensures that the data is of high quality and is free from errors, which in turn improves the performance of the AI models and XAI pipelines that are built on top of it.
- **XAI/ML/DL Datasets:** a comprehensive list of specific datasets that have been built from raw data and persisted on the Data persistence layer, ensuring that they are readily available to be fed into AI models and XAI pipelines. These datasets have undergone preprocessing to ensure that they are properly structured and optimized for their intended use cases and are fully customizable to meet the unique needs of individual users.
- **Data Persistence:** collection of historical raw data from different sources (databases, data warehouses, data lakes).

- **Data Brokering:** this layer enables the seamless and uninterrupted flow of data from various real-time sources, such as IoT sensors. It provides the necessary infrastructure to collect, store, and process these data streams in a timely and efficient manner, ensuring that they are readily available for consumption by downstream AI and XAI modules.

Edge Layer

- **Data Visualization and Data Apps:** set of consumer edge applications, referring to software applications that are deployed on edge devices, to provide services related to data visualization, device management, monitoring, control, and other similar functions. These applications can be utilized by end-users to interact with the data or devices, and include features such as analytics, reporting, or alerts.
- **Lightweight Collaborative and Explainable AI:** a lightweight version of the Collaborative and Explainable AI component that can be deployed on cloud and optimized for edge devices with limited computing power. This version leverages lightweight AI libraries and utilizes transfer learning techniques to improve training times on these devices. With this version, users can still benefit from the power of AI and XAI in their edge applications, such as data visualization, device management, monitoring, control, and more.
- **Data brokering and persistence:** this layer serves as a manager and persistent storage for the entire lifecycle of contextual information. It enables seamless and efficient management of contextual data from its creation to its storage and retrieval, ensuring its availability and reliability throughout the data's lifecycle.
- **Adapter:** this component facilitates any necessary protocol transformations required for the transportation of data and commands.
- **Agents:** this component acts as an interface between the observable layer, which includes standard and/or custom devices, external systems, etc., and the upper layers of the system. It is responsible for integrating and connecting these different components to ensure smooth communication and interaction between them.

Observable Layer

In this layer it is possible to locate external data sources. They can be both differentiated in *physical data sources* and *external data sources.*

- **Physical data sources (Products, Processes, Human, Others):** in the context of industrial applications, data can be sourced from physical objects equipped with sensors and can pertain to products and materials at every stage of the product lifecycle, industrial production processes, and human workers, as well as other domain-specific sources.
- **External data sources (Engineering Data, LCA Databases)**: external data sources, such as product data, which have already been collected and stored (i.e., in LCA Databases) are used to enhance the data flowing through the architecture.

Horizontals

- **Circular Industrial Data Space Governance Building Blocks:** a set of components essential for enabling the circular economy. The circular economy is based on the principles of reducing waste and promoting the reuse and recycling of resources. To achieve this, Industry must have access to relevant data and be able to share it securely with other stakeholders. The governance building blocks provide a framework for managing data in a standardized and secure manner, ensuring compliance with regulatory requirements and enabling collaboration between different parties. This framework includes components such as data sharing agreements, data ownership, access control, and privacy management, all of which are critical for building trust and promoting the exchange of data in a circular economy context. Overall, these blocks can be considered as a key enabler for industry to transition towards a more sustainable and circular way of operating.
- **Circular Industrial Data Space Technical Building Blocks:** a comprehensive set of technical components that support an agile, secure, and fluid flow of data and information among various parties and domains. These components can be implemented and deployed in various ways, based on different runtime frameworks, while performing a diverse set of roles within the data space. These roles include serving as fundamental building blocks that ensure data interoperability and exchange between components, such as *Agents*, *Data Brokers*, and *Connectors*. Additionally, other components support the creation of data value, like the *XAI Catalog*, while some ensure data sovereignty and trust, like the *Identity and Access Management* component. Lastly, the system provides all necessary components for connecting additional systems to the data space, like the Adapters. Within the set of technical building blocks, there are also various components dedicated to data processing, data preprocessing, and data visualization, including the *XAI Engine*.

Verticals

- **Digital models and vocabularies:** standardized data models and ontologies that enable seamless data exchange and interoperability between various components and applications. Common digital models and vocabularies development and adoption are fundamental for promoting cross-border data exchange and digital services integration across diverse sectors. This element offers a common understanding of data, allowing for the implementation of automated processes, minimizing errors, and boosting efficiency.
- **Data in motion and data at rest:** it refers to the entire spectrum of data that flows through the architecture, which encompasses data that is either at rest or in motion. Data at rest refers to information that is stored in persistent databases and can be accessed by any component within the architecture, often processed in batches. Conversely, data in motion pertains to information that is being continuously gathered from various sources, processed, and utilized in real-time, providing input to the preprocessing and processing components. By effectively handling both data at rest and in motion, this component ensures a comprehensive and dynamic approach to data management, enhancing the efficiency and effectiveness of the entire architecture.

- **Identity and Access management:** vertical that all entities and components, including individuals, organizations, machines, and other actors, are equipped with recognized identities that can be authenticated and verified, with additional information provided as needed for authorization mechanisms to enable effective access and usage control.
- **Circular Economy Applications (Green Design, Quality management, Re/De-manufacturing, Recycling):** circular economy applications are the primary focus for the entire architecture, where the convergence of business objectives and technological capabilities is realized. The implementations cover a wide range of processes, starting from the initial phases of product lifecycle, aided by AI generative design to minimize environmental impact, to optimizing processes and products, managing quality, and enabling human-robot interaction for de-manufacturing and re-manufacturing to reduce wastes, among other areas.

In the context of the Project, the reference architecture provides a framework for user interaction with digital twins, which are considered as one of the key technologies. For this reason, a dedicated viewpoint that embrace Digital Twin and Data Space has been defined and described in Figure 5-3. The nature of this interaction is bidirectional: users can not only receive predictions, explanations and insights from XAI pipelines, but also communicate with the digital twins through input commands. This allows for a more comprehensive understanding of the processes and data being analyzed and enables users to make informed decisions based on the insights gained from the digital twins. Going through details, it is possible to distinguish between:

- **Predictions**: the initial outcomes acquired by implementing predictive algorithms on Digital Twin instances within the context of the Project.
- **Explanations**: further outcomes derived from XAI pipelines, enabling stakeholders to gain knowledge about the behavior of prediction algorithms and the reasoning behind their results.
- **Insights**: further analysis of predictions and explanations from digital twin apps can provide valuable insights and new knowledge for stakeholders.
- **Commands**: users engage with digital twin applications to issue commands, utilizing the insights, predictions, and explanations they obtain from the system, which in turn influence both the physical and digital twins.

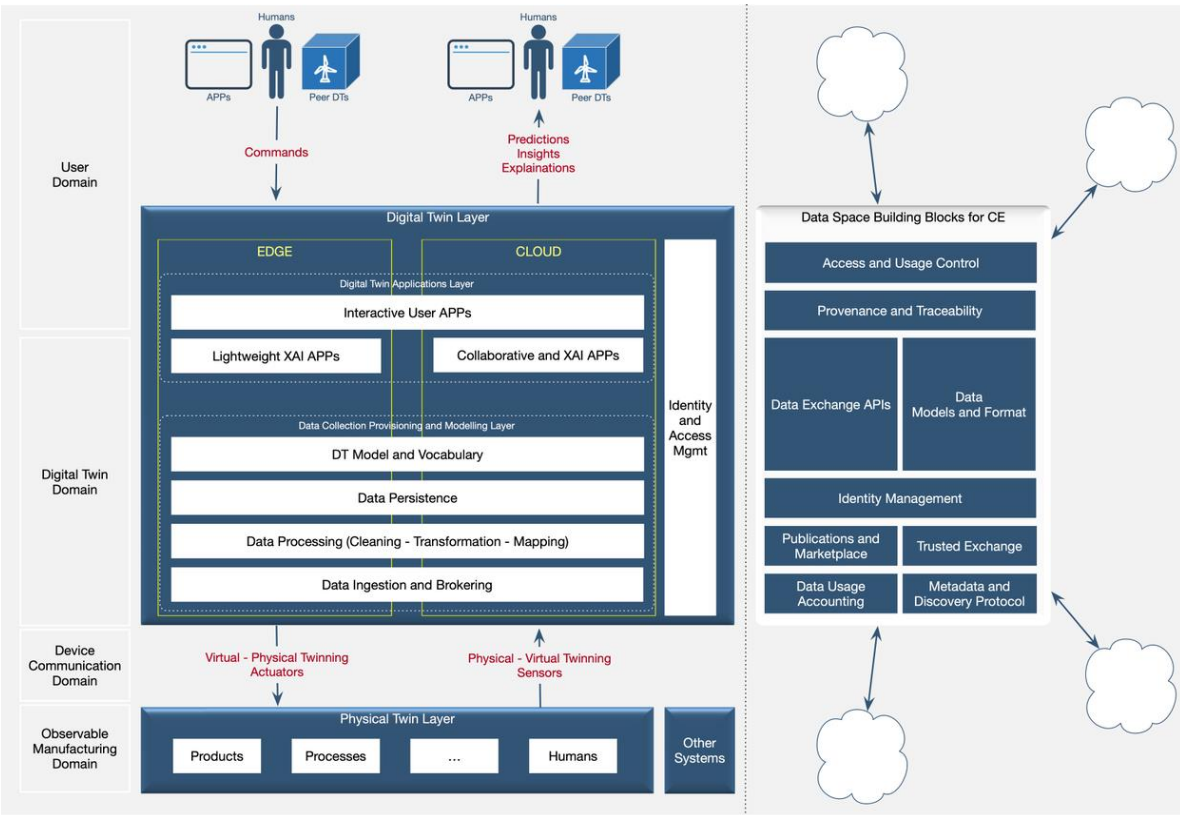

Figure 5-3: Circular TwAIn Reference Architecture - DT Viewpoint

DT Application Layer

- **Interactive User Apps**: a collection of specialized applications dedicated to Digital Twins, including (but not limited to) applications for monitoring data, interactive simulation environments, and other.
- **Collaborative and XAI Apps**: set of components already listed in 5.25.1 for creating AI models, building XAI pipelines and executing them. Users can either access the XAI Pipeline catalogue or build their own solutions using these components.
- **Lightweight XAI Apps**: this component is a subset of the Collaborative and Explainable AI applications, which are specifically designed to be executed on the edge premises, where computing resources may be limited. It is tailored to provide a more lightweight and streamlined version of these apps, while still maintaining their core functionalities of promoting collaboration and explainability in AI systems.

Data Collection and Modeling Layer

- **DT Model and Vocabulary**: set of digital twin models, which can include CAD models or other representations of a physical system, kept in synchronization with the corresponding physical twin using sensor metadata that define the so-called vocabulary. This ensures that the digital twin is an accurate and up-to-date reflection of the physical system, enabling it to be used for monitoring, simulation, and other purposes.

- **Data Persistence**: a storage system set in place for historical data that has been previously retrieved from the physical world, also known as "data at rest," and is continuously fed with continuous flows of data, or "data in motion”.
- **Data Processing**: set of components that aim to ensure the quality of Digital Twin data through various processes, such as cleaning, transformation, and mapping.
- **Data Ingestion and Brokering**: component responsible for acquiring data from sensors in the physical world for the purpose of physical-to-digital twinning, as well as issuing commands to actuators for digital-to-physical twinning. Additionally, it manages the lifecycle of context information, ensuring that the data is up-to-date and relevant.

Data Space Building Blocks for CE

- **Access and Usage Control**: data owners can manage their data assets, including determining how third parties can access and utilize the data. The reference architecture offers a range of tools and services for entities to acquire data assets from owners, while adhering to their specific constraints and requirements.
- **Provenance and Traceability**: it refers to the ability to track the origin, history, and movement of data through its lifecycle, from creation to consumption, ensuring transparency and accountability.
- **Data Exchange APIs**: a set of protocols, standards, and tools that enable interoperability and seamless data exchange between different systems and platforms. APIs facilitate the sharing of data assets, metadata, and services, ensuring that they can be easily discovered, accessed, and consumed.
- **Data Models and Format**: it refers to the way in which data is structured and represented, including the choice of data types, syntax, and semantics. Standardized data models and formats facilitate data exchange, interoperability, and reuse across different systems and applications.
- **Identity Management**: it involves managing the digital identities of users, devices, and other entities in a secure and privacy-preserving way. It includes authentication, authorization, and access control mechanisms that ensure that only authorized users and devices can access and use data.
- **Trusted Exchange**: it is the ability of establishing trust and confidence between different data stakeholders, including data owners, providers, users, and regulators. Trusted exchange mechanisms enable secure, transparent, and accountable data sharing, while protecting data privacy and confidentiality.
- **Data Usage Accounting**: a set of services to track and account for data usage, including data access, processing, and sharing. It includes mechanisms for measuring and reporting data usage, as well as for enforcing data usage policies and regulations.
- **Metadata and Discovery Protocol**: it is the process of metadata creation and management, which provides descriptive information about data assets, including their content, structure, and context. Metadata enables efficient data discovery,

retrieval, and reuse, as well as interoperability and data integration across different systems and domains.

5.2.1 Adherence with existing standards

The Circular TwAIn Reference Architecture has been contaminated by the Reference Architectures for manufacturing and running projects that haves been described in Section 4. However, RAMI4.0 heavily inspired the Circular TwAIn RA, with a clear binding between its Architecture Layer (composed by Business, Functional, Information, Communication, Integration and Asset sub-layers) and the layers/components described in the previous paragraph aiming to embrace and interconnect physical and digital world. The designed components are able to support edge-cloud analytics solutions and to describe and manage assets through standardized interfaces (i.e., compliance with Asset Administration Shell).

The Artificial Intelligence layer has been designed taking into consideration the state of the art and how AI has been implemented in the sister projects (i.e., CAPRI, AI REGIO, etc.).

5.3 Requirements and Mapping

The Circular TwAIn Reference Architecture provides Project pilots a set of features allowing them to achieve their goals. Currently (M8), pilots' requirements need to be further detailed due to the complexity of the scenarios, therefore a punctual mapping between reference architecture components and pilots' scopes will be analysed in the second iteration. Thus, according to this plan, some high-level requirements have been extracted from the analysis work already done to show how the reference architecture conforms:

- **WEEE**: electrical waste pilot has a principal aim within the Project, namely convert electrical wastes into newborn products. This aim is reachable by dismantling malfunctioning products, assessing their remaining useful life, and then deciding whether they can be reused in another component or whether they can be recycled, reused or remanufactured. This process can be improved in terms of efficiency and safety thanks to an AI-enhanced human in the loop process. In particular, the manufacturing process can be divided into three stages, one of which (treatment phase) can be improved thanks to the application of the reference architecture. In fact, it is possible to accelerate the classification and diagnosis tasks using XAI pipelines, thus exploiting digital twin technology to gain greater insight into components and their sub-parts. Thanks to the visualization layer, a sequence of disassembly steps can be shown to help operators in their work. Furthermore, by tracking each operation thanks to the RA data collection system, it might be possible to design a XAI-enhanced performance evaluator to assess the process improvements achieved thanks to the use of the Circular TwAIn framework.
- **BATTERY**: the battery pilot aims to assess the added value that is possible to generate by recycling lithium-ion battery packs from automotive industry. The Reference Architecture can support this pilot by improving the de-manufacturing processes through implementation of digital battery twins and artificial intelligence-enhanced processes. In this pilot, electrical testing on battery is a dangerous process involving high voltages. Through the use of XAI pipelines and digital twins, the accuracy of those tests can be improved, resulting in a more robust estimate of battery life. Moreover, by collecting and exploiting market data, XAI-enhanced

market-oriented decision support systems can be designed to assess the increase in business value resulting from previous decisions.

- **PETROL-CHEMICAL**: this pilot aims to improve its production process by reducing waste and CO2 emissions, as well as energy consumption. The production process is complex and relies on many variables, thus requiring complex control systems. By leveraging digital twins of processes and human-machine interaction, it is possible to use the reference architecture to design a XAI-enhanced distributed control system allowing the collection of real time data, analysis and explanation necessary to operators to intervene in production process when necessary. Furthermore, real-time process values are monitored by DCS (distributed control system), ESD (emergency shutdown system) also by process operators via human-machine interfaces. If needed operators have the authority to intervene in the process set points manually

6 Conclusion and Future Outlook

D3.1 - Conceptual Framework and Reference Architecture - 1st version reports on approaches to Resilient and Circular Manufacturing in Value Chains (T3.1), on methods and solutions to support the development of trustworthy and explainable AI and collaborative systems (T3.2), on the technological background for the design of the Circular TwAIn Reference Architecture, and the Circular TwAIn Reference Architecture (T3.3).

Sections 2 and 3 provided the required background to understand the common approaches and methodologies to resilient and circular manufacturing, and the best practices on how to develop trustworthy AI. Approaches and methodologies presented in background sections are meant to drive the implementation of AI modules to support CE in Circular TwAIn, and have been considered in the design of the Circular TwAIn Reference Architecture.

The first version of the Circular TwAIn Reference Architecture was presented, complete with the detailed specification of all its functional elements, subsystems and main interaction rules and principles. The present document will be complemented by other deliverables of WP4 and WP5, where the components will be deep dived providing information also about their development and deployment.

Building on the knowledge created by the technology exploration activities, along with the acquired knowledge of the use cases and user requirements, the Circular TwAIn Reference Architecture was specified through a top-down approach (for breaking down the overall system into its most basic of components, identifying pertinent subsystems and their functionalities along the way), followed by a bottom-up specification of each eventually identified basal component. Interdependencies between identified components and subsystems have been recorded so as to guide the implementation of the respective modules by the development teams across the technical Work Packages.

Moreover, this document maps the core components depicted in Figure 5-2: Circular TwAIn Reference Architecture, over the high-level requirements carried out by the activities of WP2 and WP6.

The final achievements of the first three tasks of WP3 will be documented in D3.4 - Conceptual Framework and Reference Architecture - 2nd version (M27).

References

[1] Dell'Ambrogio, S. et al. (2020). TREASURE: leading the TRansion of the European Automotive SUpply chain towards a circulaR futurE" (GA number: 101003587). https://www.treasureproject.eu/

[2] Frishammar, J., & Parida, V. (2019). Circular business model transformation: A roadmap for incumbent firms.California Management Review,61(2), 5–29.

[3] Evans, S., Vladimirova, D. Holgado, M., Van Fossen, K., Yang, M. Silva, E. A., & Barlow, C. Y. (2017). Business model innovation for sustainability: Towards a unified perspective for creation of sustainable business models. Business Strategy and the Environment,26(5),597–608. https://doi.org/10.1002/bse.1939

[4] Linder, M., & Williander, M. (2017). Circular business model innovation: Inherent uncertainties. Business Strategy and the Environment,26(2),182–196. https://doi/10.1002/bse.1906

[5] Woldeyes, Tirufat Dejene & Muffatto, Moreno & Ferrati, Francesco. (2022). Emerging Business Models for Circular Economy: A Systematic Literature Review. European Conference on Innovation and Entrepreneurship. 17. 599-607. 10.34190/ecie.17.1.442.

[6] Arup 2016, The Circular Economy in the Built Environment, London, retrieved February 22th 2023, https://www.arup.com/perspectives/publications/research/section/circular-economy-in-the-built-environment

[7] Accenture. (2014). Circular Advantage Innovative Business Models Technologies Value Growth

[8] Bocken, de Pauw, I., Bakker, C., & van der Grinten, B. (2016). Product design and business model strategies for a circular economy. Journal of Industrial and Production Engineering, 33(5), 308-320.

[9] Geissdoerfer, M., Pieroni, M. P. P., Pigosso, D. C. A., & Soufani, K. (2020). Circular business models: A review. Journal of Cleaner Production, 277.

[10] Konietzko, J., Bocken, N., & Hultink, E. J. (2020). A Tool to Analyze, Ideate and Develop Circular Innovation Ecosystems. Sustainability, 12(1).

[11] BSI. (2017). Framework for Implementing the Principles of the Circular Economy.

[12] https://hbr.org/2021/07/the-circular-business-model, March 2023.

[13] Potting, J., Hekkert, M., Worrell, E., & Hanemaaijer, A. (2017). Circular economy: Measuring innovation in the product chain. PBL Publishers.

[14] Saidani, Michael, et al. "A taxonomy of circular economy indicators." Journal of Cleaner Production 207 (2019): 542-559.

[15] Wilson, M., Paschen, J. and Pitt, L. (2022), "The circular economy meets artificial intelligence (AI): understanding the opportunities of AI for reverse logistics",

Management of Environmental Quality, Vol. 33 No. 1, pp. 9-25. https://doi.org/10.1108/MEQ-10-2020-0222

[16] Fraga-Lamas P, Lopes SI, Fernández-Caramés TM. Green IoT and Edge AI as Key Technological Enablers for a Sustainable Digital Transition towards a Smart Circular Economy: An Industry 5.0 Use Case. Sensors. 2021; 21(17):5745. https://doi.org/10.3390/s21175745

[17] Tamil Selvan Ramadoss, Hilaal Alam, Ramakrishna Seeram (2018), "Artificial Intelligence and Internet of Things enabled Circular economy". The International Journal of Engineering and Science (IJES), Vol. 8 No. 9, pp. 53-63.

[18] Roberts, H., Zhang, J., Bariach, B. et al. Artificial intelligence in support of the circular economy: ethical considerations and a path forward. AI & Soc (2022). https://doi.org/10.1007/s00146-022-01596-8

[19] Baker-Brunnbauer, J. (2021). TAII Framework for Trustworthy AI Systems. ROBONOMICS: The Journal of the Automated Economy, 2, 17.

[20] Floridi, L., Cowls, J., Beltrametti, M. et al. AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations. Minds & Machines 28, 689–707 (2018). https://doi.org/10.1007/s11023-018-9482-5

[21] https://ec.europa.eu/futurium/en/system/files/ged/a2-schweichhart-reference_architectural_model_industrie_4.0_rami_4.0.pdf, February 2023.

[22] https://www.iiconsortium.org/iira/, February 2023.

[23] https://docs.internationaldataspaces.org/knowledge-base/ids-ram-4.0, February 2023.

[24] https://www.fiware.org/about-us/smart-industry/, February 2023

[25] Jacoby, M.; Jovicic, B.; Stojanovic, L.; Stojanović, N. An Approach for Realizing Hybrid Digital Twins Using Asset Administration Shells and Apache StreamPipes. *Information* **2021**, *12*, 217. https://doi.org/10.3390/info12060217

[26] https://github.com/FraunhoferIOSB/FAAAST-Service

[27] Jacoby, Michael, Volz, Friedrich, Weißenbacher, Christian, Stojanovic, Ljiljana and Usländer, Thomas. "An approach for Industrie 4.0-compliant and data-sovereign Digital Twins: Realization of the Industrie 4.0 Asset Administration Shell with a data-sovereignty extension" at - Automatisierungstechnik, vol. 69, no. 12, 2021, pp. 1051-1061. https://doi.org/10.1515/auto-2021-0074

[28] Leila Saari, Vafa Järnefelt, Katri Valkokari, Jorge Tiago Martins, Federica Acerbi. Towards Sustain- able Manufacturing through Collaborative Circular Economy Strategies. 22nd IFIP WG 5.5 Working Conference on VIRTUAL ENTERPRISES, PRO-VE 2021, Nov 2021, Saint-Etienne, France. 10p, 10.1007/978-3-030-85969-5_33 . emse-03339428.

[29] J. Soldatos et al., "A digital platform for cross-sector collaborative value networks in the circular economy," Procedia Manuf., vol. 54, pp. 64–69, Jan. 2021, doi: 10.1016/j.promfg.2021.07.011.

Annex I

Table 6-1 below reports the list of circular indicators, classified accordingly to the categorization showed in Section 2.3.1

Table 6-1: Circular Indicators

Circularity Indicators	Description (working principles)	Evaluation format	Dimensionality	Evaluation Method	Data Required (Overview)	Purposes				Sources
						Information (Tracking Progress, Benchmaking)	Decision-Making (Action-Oriented)	Communication (Intern, Extern)	Learning (Education, Awareness)	
Product-Level Circularity Metric (PCM)	Formula: C = economic value of recirculated parts / economic value of all parts ; where circularity (C) is defined as the fraction of a product that comes from used products (i.e. from closed- or open-looped cycles)	Formula	Single	Quantitative [%]	Bill of Materials plus different costs Involved, to estimate economic value.		x	x		(Linder et al., 2017) Linder, M., Sarasini, S. and van Loon, P. (2017), A Metric for Quantifying Product-Level Circularity. Journal of Industrial Ecology, 21: 545–558. doi:10.1111/jiec.12552
Circular Economy Index (CEI)	Formula: Ratio between the material value obtained from recycled products and the one entering the recycling facility (CEI measures circularity in	Formula	Single	Quantitative [%]	To compute the CEI, it is necessary to know detailed information (values) of the components and		x			(Di Maio and Rem, 2015) A robust indicator for promoting circular economy through recycling. Journal of Environmental Protection 6, 1095-1104 http://dx.doi.org/10.4236/jep.2015.610096

	terms of the ratio of recycled material value from EoL products compared to total material value in recycling processes needed to produce new versions of the same product.) (Measures recycling rates, excluding all other circular economy effects and loops.)				materials contained in each EoL product entering the recycling facilities and how they end up in the recycled raw materials.					
Circularity Index (CI)	Formula: α = recovered end-of-life (EOL) material / total material demand; β = 1 – energy required to recover material / energy required for primary production; Circularity Index (CI) = αβ, maximum value = 1	Formula	Multiple	Quantitative [%]	Production & EoL recycling data	x		x		(Cullen, 2017) Cullen, J. M. (2017), Circular Economy: Theoretical Benchmark or Perpetual Motion Machine?. Journal of Industrial Ecology, 21: 483–486. doi:10.1111/jiec.12599 Haas, W., F. Krausmann, D. Wiedenhofer, and M. Heinz. 2015. How circular is the global economy?: An assessment of material flows, waste production, and recycling in the European Union and the world in 2005. Journal of Industrial Ecology 19(5): 765–777.
Recycling indicator	IW is an indicator on	Formula	Single	Quantitative [%]	Number of output	x	x			Nelen, Dirk, et al. "A multidimensional

set: Weight recovery of target material(s) (IW)	effectively recovered weight is proposed that is calculated as the sum of the weights of the target materials in each recycled output fraction divided by the total material weight of the input				fractions from the recycling process, number of material present in the input of recycling process, weight of target materials in output, weight of material present in the input of recycling process					indicator set to assess the benefits of WEEE material recycling." Journal of Cleaner Production 83 (2014): 305-316.
Recycling indicator set: Recovery of scarce materials (IS)	IS is an indicator that reflects the criticality of recycled target materials in relation to the total criticality of materials present in the input of the recycling process	Formula	Single	Quantitative [%]	Number of output fractions from the recycling process, number of material present in the input of recycling process, weight of target materials in output, weight of material present in the input of recycling	x	x			Nelen, Dirk, et al. "A multidimensional indicator set to assess the benefits of WEEE material recycling." Journal of Cleaner Production 83 (2014): 305-316.

					process, econimic importance of the material, supply risk of the material					
Recycling indicator set: Closure of material cycles (IC)	IC is an indicator to measure material cycle closure.	Formula	Single	Quantitative [%]	Number of output fractions from the recycling process, number of material present in the input of recycling process, weight of target materials in output, weight of material present in the input of recycling process, current market price of output, current market price of the materiale present in the EEE	x	x			Nelen, Dirk, et al. "A multidimensional indicator set to assess the benefits of WEEE material recycling." Journal of Cleaner Production 83 (2014): 305-316.
Recycling indicator set:	IE ha the objective to assess the	Formula	Single	Quantitative [%]	Number of output fractions	x	x			Nelen, Dirk, et al. "A multidimensional indicator set to assess

Avoided environmental burdens (IE)	avoided environmental impact that can be achieved by recycling materials.				from the recycling process, number of material present in the input of recycling process, weight of target materials in output, weight of material present in the input of recycling process, environmental burden associated with the production of the material that is avoided by the recucled output, environmental burden associated with the production of the material presente in the EEE					the benefits of WEEE material recycling." Journal of Cleaner Production 83 (2014): 305-316.
Recyclability Benefit Rate (RBR)	This indicator is defined as the ratio of the potential	Formula	Single	Quantitative [various]	Mass of the materials in each part of the product,	x	x	x		Huysman, Sofie, et al. "The recyclability benefit rate of closed-loop and open-loop systems: A

	environmental savings that can be achieved from recycling the product over the environmental burdens of virgin production followed by disposal				the impact of disposing 1 kg of each material in each part of the product, the impact of producing 1 kg of virgin material in each part of the product, the impact of producing 1 kg of the recycled material in each part of the product, the impact of manufacturing the product, the impact of the use phase of the product, number of materials in the product, number of parts of the product, the recycling rate of the each material in each part of the product					case study on plastic recycling in Flanders." Resources, Conservation and Recycling 101 (2015): 53-60.
Material Reutilizatio	Indicator showing the content of	Formula	Single	Quantitative [%]	Percentage of recycled or rapidly	x		x		Cradle to Cradle Products Innovation Institute (2016)

n Score (MRS)	recycled or recyclable material in a product				renewable product content and percentage of product recyclable or biodegradle/ compostable					
Value-based Resource Efficiency Indicator (VRE)	It aims at introducing the economic value of the materials embedded in consumers products as the property to be measured and accounted.	Formula	Single	Quantitative [%]	Material value recycled from EOL products, material value needed for (re-) producing EOL products	x	x	x		Di Maio, Francesco, et al. "Measuring resource efficiency and circular economy: A market value approach." Resources, Conservation and Recycling 122 (2017): 163-171
End-of-life Indices: Reuse index	The Reuse index considers the possibility of a given component being reused in the same product or in similar products	Formula	Single	Quantitative [%]	Percentage of the original value of the part under analysis, value of the virgin material, value of the manufacturing operations, cost of reverse logistic, cost of selective disassembly operations, cost of the cleaning operations	x	x	x		Favi, Claudio, et al. "A design for EoL approach and metrics to favour closed-loop scenarios for products." International Journal of Sustainable Engineering 10.3 (2017): 136-146.

End-of-life Indices: Remanufacture index	The Remanufacture index evaluates the possibility of a component being regenerated on the basis of different cost types and revenues involved in the 'remanufacture loop'	Formula	Single	Quantitative [%]	Percentage of the original value of the part under analysis, value of the virgin material, value of the original manufacturing operations to produce the part non necessary for remanufacture, cost of reverse logistic, cost of selective disassembly operations, cost of the cleaning operations, cost of addictional remanufacture operations	x	x	x		Favi, Claudio, et al. "A design for EoL approach and metrics to favour closed-loop scenarios for products." International Journal of Sustainable Engineering 10.3 (2017): 136-146.
End-of-life Indices: Recycling index	The Recycling index compares the difference between the production costs for virgin materials and the revenues coming from the recycling	Formula	Single	Quantitative [%]	Value of the recycled materials, value of the energy saved by not producing virgin materials, cost of	x	x	x		Favi, Claudio, et al. "A design for EoL approach and metrics to favour closed-loop scenarios for products." International Journal of Sustainable Engineering 10.3 (2017): 136-146.

	process. In particular, it takes into account the energy savings resulting from the recycling process of a material and the revenues from recycled material				reverse logistics, cost of destructive disassembly operations, cost of the cleaning operations					
End-of-life Indices: Incineration index	The Incineration index establishes whether particular combinations of materials can be directly incinerated for energy production	Formula	Single	Quantitative [%]	Value of energy gained from combustion, cost of reverse logistics, cost of destructive disassembly operations	x	x	x		Favi, Claudio, et al. "A design for EoL approach and metrics to favour closed-loop scenarios for products." International Journal of Sustainable Engineering 10.3 (2017): 136-146.
Sustainable Circular Index (SCI)	The Sustainable Circular Index is for an individual company and is formed by four dimensions (economic, social, environmental, and circularity).	Formula	Multiple	Quantitative [various]						Azevedo, Susana Garrido, Radu Godina, and João Carlos de Oliveira Matias. "Proposal of a sustainable circular index for manufacturing companies." Resources 6 .4 (2017): 63.)
Linear Flow Index for Product Families	Measures the proportion of material flowing linearly, that is, from virgin materials and up to unrecoverable waste	Formula	Multiple	Quantitative [%]	Mass of virgin feedstock used to manufacture a product, mass of unrecoverabl	x	x			Mesa, Jaime, Iván Esparragoza, and Heriberto Maury. "Developing a set of sustainability indicators for product families based on the circular economy model." Journal

					e waste associated with a product manufacturing, total mass of the product, mass of unrecoverable waste generated when producing recycled feedstock for the product, mass of unrecoverable waste generated in the process of recycling parts for the product					of cleaner production 196 (2018): 1429-1442.
Combination Matrix (CM): Circularity	Combination matrix is a matrix that combines the circularity and longevity of a product. Circularity is expressed as the number of times a resource is used in a product system.	Formula	Multiple	Quantitative [number of times]	Number of times the resource is refurbished, number of times the resource is recycled	x				Figge, Frank, et al. "Longevity and circularity as indicators of eco-efficient resource use in the circular economy." Ecological economics 150 (2018): 297-306.
Combination Matrix	Combination matrix is a matrix that	Formula	Multiple	Quantitative [time]	The amount of time during which	x				Figge, Frank, et al. "Longevity and circularity as indicators of eco-

(CM): Longevity	combines the circularity and longevity of a product. Longevity is the length of time that a resource is used				a product is used initially, the refurbished lifetime, the recycled lifetime					efficient resource use in the circular economy." Ecological economics 150 (2018): 297-306.
Effective Disassembly Time	Indicator expressing the effective disassembly time of a product	Formula	Single	Quantitative [time]	Standard disassembly time, corrective factore related to the chosen de-manufacturing conditions	x	x		x	Marconi, Marco, et al. "Applying data mining technique to disassembly sequence planning: a method to assess effective disassembly time of industrial products." International Journal of Production Research 57.2 (2019): 599-623.
Old scrap Collection Rate (CR)	The CR express how much of the end-of-life material is collected and enters the recycling chain	Formula	Single	Quantitative [%]	EOL materials collected for recycling per product, EOL products	x		x		Graedel, Thomas E., et al. "What do we know about metal recycling rates?." Journal of Industrial Ecology 15.3 (2011): 355-366.
Circularity of Material Quality (QC)	The material quality indicator is based on the energy use of recycled products versus their counterparts produced from primary material inputs only. It cover the environmental pillar of the sustainability.	Formula	Single	Quantitative [-]	Kg of secondary material that can be made from recycling 1 kg of primary material, ratio of diluting material to primary material to be recycled, direct life	x	x			Steinmann, Z. J. N., M. A. J. Huijbregts, and L. Reijnders. "How to define the quality of materials in a circular economy?." Resources, Conservation and Recycling 141 (2019): 362-363.

					cycle energy requirement for producing the material, energy required for cleaning, embodied cradle-to-gate life cycle energy in the primary materials required for dilution, cradle-to-gate life cycle energy required for producing 1 kg of primary material.					
Circular-process feedstock intensity (CPFI)	It quantifies raw material consumption and is the ratio of the total amount of the main raw materials used to the total amount of useful outputs	Formula	Single	Quantitative [%]	Total mass of primary feedstock fed into the process (kg); total mass of the target end-product synthesised in a process (kg); total mass of any useful co-products synthesised in a process (kg); total		x	x		Lokesh, Kadambari, et al. "Hybridised sustainability metrics for use in life cycle assessment of bio-based products: Resource efficiency and circularity." Green Chemistry 22.3 (2020): 803-813

					mass of the material recovered /recycled from production waste or EoL (kg).					
Circular-process waste factor (CPWF)	It measures the ratio of the total mass (kg) of solid, liquid or gaseous waste, generated as process wastes or lost from the system via leaks or spills, with respect to the total mass (kg) of the end-product and co-products.	Formula	Single	Quantitative [%]	Total mass of waste generated from the production process (kg); total mass of the end-product generated from the process (kg); total mass of useful co-products generated (kg); total mass of the recovered and recycled product		x	x		Lokesh, Kadambari, et al. "Hybridised sustainability metrics for use in life cycle assessment of bio-based products: Resource efficiency and circularity." Green Chemistry 22.3 (2020): 803-813
Resource efficiency indicator for electrical and electronic equipment (RE EEE)	Resource efficiency not only related to the mechanical technology, but also has a relation with the used condition from human beings. Considering environmental	Formula	Single	Quantitative [%]	TMR (total amount of crude metals, ores, soils, removed surface soils, etc.) to obtain a unit amount of refined metals.		x	x		Juntao, Wang, and Nozomu Mishima. "Development of Resource Efficiency Index for Electrical and Electronic Equipment." Procedia CIRP 61 (2017): 275-280.)

	impacts along with utilization of resources, the coefficient of environmental impacts defined before need to be covered while evaluate resource efficiency.				Considering: TMR of the resources contained in the product; TMR of resources needed to produce the product; TMR of the resources really used in the product along with time; TMR of the resources contained in each function (i) of the product; TMR of the resources needed to produce the product; TMR of the resources recycled; etc.. (see paper for more)						

Funded by
the European Union

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 101058585