D2.3 - FRAMEWORK FOR AI&BD MATURITY LEVEL ASSESSMENT

Project details

Project Title	**Artificial Intelligence and Big Data CSA for Process Industry Users, Business Development and Exploitation**
Project Type:	CSA
Project Acronym	AI CUBE
Grant Agreement No.	958402
Duration	24 Months
Project Start Date	September 1, 2020

Document details

WP:	**2**	**WP Leader:**	**CNR (Beneficiary 5)**
WP Title:	Industry consultation and AI&BD framework for maturity level		
Deliverable No.	D2.3.		
Deliverable Title	Framework for AI&BD maturity level assessment		
Dissemination level	Public		
Written By	CNR (Beneficiary 5)		
Contributing beneficiaries	PNO (Beneficiary 1), IRIS (Beneficiary 4), IML (Beneficiary 3), ZLC (Beneficiary 2)		
Approved by	PNO (Beneficiary 1)		

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 958402

Status	Version 6
Date	28/05/2021

Deliverable information

Status (F: final; D: draft; RD: revised draft):	Final
Planned delivery date	30/04/2021 (M8)
Actual delivery date	30/05/2021 (M9)
Dissemination level: (PU = Public; PP = Restricted to other program participants; RE = Restricted to a group specified by the consortium; CO = Confidential, only for members of the consortium)	PU
Type: Report, Website, Other, Ethics	Report

Document History

Version	Date (MM/DD/YYYY)	Created/Amended by	Changes
01	28/04/2021	Rosanna Fornasiero, Amin Falsafi	Draft version of the deliverable
02	30/04/2021	Chiara Eleonora De Marco	Review and comments
03	13/05/2021	Rosanna Fornasiero, Amin Falsafi	Reviewed version
04	25/05/2021	Chiara Eleonora De Marco	General check on final draft
05	26/05/2021	Rosanna Fornasiero	Inclusion of glossary and final version release
06	28/05/2021	Rosanna Fornasiero	Final draft edits

Quality check review

Reviewer (s)	Main changes
Chiara Eleonora De Marco	Content clarity and quality check General check of consistency and editing
Ron Weerdmeester	Quality Check

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List of abbreviations and definitions

Please complete, in alphabetic order, with the abbreviations used in the document

Abbreviation	Definition
AI	Artificial Intelligence
BD	Big Data
BDA	Big Data Analytics
CDO	Chief Data Officer
CEO	Chief Executive Officer
CPS	Cyber-Physical Systems
CTO	Chief Technical Officer
DoA	Description of Action
DRIP	Data Rich and Information Poor
EC	European Commission
ELSI	Ethical, Legal, Social Issues
H2020	Horizon 2020
IT	Information Technology
MLA	Maturity Level Assessment
ML	Machine Learning
SPIRE	Sustainable Process Industry through Resource and Energy Efficiency

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1. Executive Summary

This deliverable aims to describe the work conducted in T2.2 within WP2. In particular, the goal is to describe the conceptual framework developed for the Maturity Level Assessment (MLA) of the application of AI and BD technologies in the process industry, and the instantiation of the model by mean of a questionnaire tools developed in operationalizing the AI-CUBE MLA. Different MLA models available in literature have been analysed and compared in order to gather information about which are the dimensions to be considered, how they interact with each other and which are the areas of analysis to be considered. The AI-CUBE MLA framework is structured along 4 domains: strategy, governance, people, and technology. The MLA is operationalized in a questionnaire that will be run in WP3 to collect the point of view of users of AI/BD, i.e. companies from the SPIRE sectors, and providers of AI/BD, i.e. IT companies, associations, consultancy companies. These analyses will result in the comprehensive output of the Technological Maturity Level, a metric based on the assessment of the application of digital technologies against different processes in different sectors, also taking into consideration the maturity in dealing with the ELSI (Ethical, Legal, Social Issues).

1. Project Introduction

AI-CUBE seeks to enhance the understanding of different digital technologies related to artificial intelligence (AI) and big data (BD) applied in process industries for 8 SPIRE industrial sectors (cement, ceramics, chemicals, engineering, minerals and ores, non-ferrous metals, steel, water). Therefore, a close collaboration with industry is mandatory to achieve in-depth insights into possible application areas of AI for processes, technology, sensor applicability and assessment of their level of penetration. The overall project approach is based on the development of a 3-dimensional conceptual matrix based on: 1) AI and BD technologies 2) Application areas (activities and industrial processes) 3) SPIRE sectors.

AI-CUBE's main goal is to identify the use and penetration of AI and BD in each of the process industries and organisational processes, as a basis for cross-sectorial knowledge and technology transfer and to design business case-oriented roadmaps for the European process industries of the future. The Maturity Level of the use and implementation of AI and BD in the different process industries is therefore instrumental to be able to develop roadmaps, and guidelines for their implementation.

Industrial stakeholders and associations will validate consolidated roadmaps ensuring solution feasibility and benefits for the European industrial community. A crosslinked vision over process industry sectors should facilitate cooperation and boost technologies deployment at their full potential. An in-depth consultation with industry (association, representatives, companies) will provide an overview of current AI and BD algorithms application, identifying exploitable synergies among sectors. A deep study of the application areas in planning and operations within other industrial sectors facilitates a gap analysis, propitiating knowledge sharing among processes and sectors. A Multi-Actor Multi-Criteria analysis will obtain a widely supported and consensus-based action plan for industrial consultation. This will allow the inclusion of a broad stakeholder community representing the main industry actors throughout all the SPIRE sectors, with which the project consortium has strong connections that will support sector integration and stakeholders' engagement.

2. Objectives of this Deliverable

The objective of this deliverable is to describe the work conducted in T2.2 within WP2 and in particular the conceptual framework developed for the evaluation of the maturity level of the process industry in the application of AI and BD technologies and practices, assessing to what extent they are used through a questionnaire tool developed to operationalize and put into practice the conceptualization of the AI-CUBE MLA. Based on the work in WP1, namely the definition of a taxonomy of the different types of AI and BD technologies, and the confirmation of the processes to be considered in the AI-CUBE project activities, it is necessary to identify a system to assess the different degrees of application of each AI and BD technology, taking into consideration processes and activities. In the literature some systems are already available to evaluate the overall digital maturity that make possible obtaining the status of a company in terms of its digitalisation with a benchmark comparison. This deliverable's goal is to analyse these systems and develop a new framework specifically for AI and BD to: (i) provide an impartial and complete evaluation system updated to the MLA state-of-the-art; (ii) understand the industrial needs in terms of technologies; (iii) identify a cross-sectorial comparative system to define maturity level and, furthermore, suggest new actions for improvement. The framework will take into consideration not only technological maturity, special attention will be devoted to considering also criteria to be applied in evaluating the maturity concerning the ELSI (Ethical, Legal, Social Issues). This framework will be applied in WP3.

3. Methodology and Approach

In order to compile and review the information contained in this deliverable, we applied a methodology consisting of the following steps, adapting the phases showed in Fig. 1:

(i) Perform a literature search on the models and methodologies already available to define a MLA framework;

(ii) Perform a literature review on the most important MLA models available, taking into consideration in particular the models developed for AI and BD technologies application, independently from the application sector;

(iii) From the results of (i) and (ii), and having in mind the objectives of the AI-CUBE project, we extract the most important domains to be analysed to establish a Maturity Level specific for AI and BD technologies, or application based on some domains of analysis;

(iv) After this, we identify the methodology of application of the MLA framework defining the questionnaire tool to be used to assess the digital technology application maturity along the relevant domains, addressed to two categories of respondent, i.e. companies from two different categories: AI/BD users or providers;

(v) Finally, a scoring system has been developed to quantify the AI and BD Maturity Level based on the aggregated answers provided to the questionnaire tool of our MLA system.

4. MATURITY LEVEL ASSESSMENT MODELS – STATE-OF-THE-ART

Maturity Level Assessment (MLA) Models have proved to be important instruments to support the positioning of organizations in a specific comparative framework and help find better solutions for change (Becker et al., 2009). MLA Models have become a well-established tool also in the area of digitalisation to support corporate management in complex and novel technology transformation processes (Hausladen and Schosser, 2020), and understand the gaps in the development path.

MLA models can be considered "multi-stage models that describe typical patterns in the development of organizational capabilities" (Comuzzi and Patel, 2016). For each maturity level, the MLA model describes corresponding stages for relevant domains. These stages should be logically connected and generalizable to identify the correct maturity level of an organization (Hausladen and Schosser, 2020).

The basic principle of a MLA model is to describe maturity stages across different relevant domains (Roglinger et al., 2012). The definition of a MLA framework is based on multiple steps as represented in Figure 1.

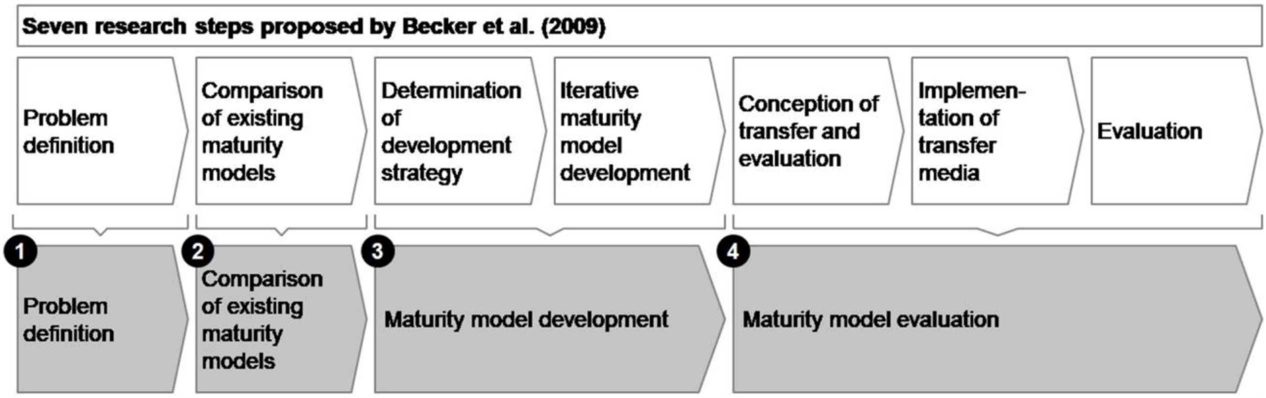

Figure 1. Research phases for MLA design (Hausladen and Schosser, 2020)

4.1 PROBLEM DEFINITION

As from Table 1, the problem definition phase is based on:

- *Audience*: who are the intended stakeholders of the MLA model (EU Commission, SPIRE association, sector associations, companies, academics).
- *Methods of application*: how the model can be applied to different organizational structures using tools such as questionnaires and surveys for self-assessment, interviews and workshops with support of third parties or certified practitioners. The AI-CUBE MLA will be applied through a purposely developed questionnaire tool, reported in the Annexes to this deliverable.
- *Drivers of application*: drivers can be both external to a single company or internal. in the AI-CUBE project, the drivers are mainly external because the need for an MLA was generated by the EU commission.

- *Respondents*: who is intended to respond a tool in the form of a questionnaire, survey etc. to gather needed data and information fuelling the application of the MLA model.
- *Area of application*: which area the MLA model covers (regional vs multi-regional, 1 entity vs multiple entities)

To meet audience needs, the model design needs to strike an appropriate balance between a reality which is often complex and the need for model simplicity. A common design principle is to represent maturity as a number of cumulative stages where higher stages build on the requirements of lower stages. The number of stages may vary from model to model, but it is important that the final stages are distinct and well-defined, and the existence of a logical progression through stages. Identification of domain components is critical for complex domains as this enables a deeper understanding of maturity, without which the identification of specific improvement strategies is difficult. The goal is to attain domain components and sub-components that are mutually exclusive and collectively exhaustive (De Bruin, T., et. al., 2005).

Table 1. Features for the maturity model definition

Criterion	Characteristic		
Audience	Internal		External
	Executives, Management		Auditors, Partners
Method of Application	Self Assessment	Third Party Assisted	Certified Practitioner
Driver of Application	Internal Requirement	External Requirement	Both
Respondents	Management	Staff	Business Partners
Application	1 entity / 1 region	Multiple entities / single region	Multiple entities / multiple region

4.2 COMPARISON OF EXISTING MLA FRAMEWORKS

In the literature, there are some MLA frameworks to evaluate the overall digital maturity level of a company, allowing to obtain the digitalisation level of a company with a benchmark comparison to the rest of the population analysed. These are systems that gain importance as far as they manage to involve larger number of cases. For example, the assessment of the DREAMY model (Digital REadiness Assessment MaturitY model), developed by the Industry 4.0 observatory of Politecnico di Milano, is based on business processes grouped in strategic areas for the digital transformation. Another model is the Industry 4.0 Maturity Model developed by Schumacher et al., grouping maturity items into nine dimensions: strategy, leadership, customers, products, operations, culture, people, governance, technology.

To go beyond these MLA models for digitalization, there are already some specific initiatives related to either AI or BD analysed in separate models and applied to different industrial sectors, but limited emphasis is given to the peculiarities of the process industry. In this section, we analysed some of the most recent MLA models to understand how they are structured, and which are the practices we can take inspiration from to develop the AI-CUBE MLA.

Comuzzi and Patel, (2016) develop a model to support organisations in the realisation of the value created by Big Data. The proposed model answers the call for research on Big Data to abstract from technical issues, focusing on the business implications of Big Data initiatives. The MLA model is developed following a qualitative approach based on literature analysis and semi-structured interviews with domain experts. The completeness and usefulness of the model is evaluated qualitatively by practitioners, whereas the applicability of the model is evaluated through BD maturity assessments in three real-world organisations.

The model is based on five domains and, for each of them, a second level has been defined as follows:

- **Strategic alignment:**
    - ***Strategy**,* refers to whether BD becomes embedded in the corporate strategy and if it becomes a strategic imperative for the organisation around which the corporate strategy is defined.
    - ***Processes**,* maturity is determined mainly by the level of penetration of BD technology into operational and decision-making processes.
- **Data:**
    - ***Analytics***, whose maturity is evaluated by the scope of the analytics software applications used by the organisation and by their ease of use as perceived by intended users.
    - ***Data Management*** focuses on the identification of data types and sources and the definition of policies for data naming, usage, security and privacy, and data quality.
- **Organisation:** focuses on understanding individual and collective attitudes towards BD:
    - ***People***, maturity increases with staff being proactive in experimenting with BD technology and initiatives and creating positive feedback loops to share positive experiences.
    - ***Culture***, maturity is determined by the presence of business and IT sponsors and by the level of trust that the organisation has in the outcomes of BD initiatives.
- **Governance** is defined by and only for the IT function. Maturity increases with the definition of organisational entities dedicated to the supervision of BD initiatives and results, such as board and steering committee, and by formally defining the skills required. These skills encompass the ability of the data scientist to understand the business implications of BD initiatives in the use cases relevant to the organisation target of the maturity assessment (no sub-domains for governance).
- **Information technology:**
    - ***IT infrastructure*** sub-domain is driven by the scope of technology to store and process BD. Low levels of maturity entail an IT infrastructure based on traditional relational technology on top of a centralised data warehouse. Implementation of the full spectrum of BD technology (see Chen and Zhang, 2014) defines the higher levels of maturity: BDA tools are actively used to optimise the IT infrastructure load and to predict future needs.
    - ***Information Management*** sub-domain: maturity of BD is defined by the extent to which data available within the organisation can be easily associated to the operational/decision-making process that they support and by the level of cooperation between the IT function and other business functions in understanding what data are actually useful for the organization

In Pringle and Zoller (Ovum), (2018), the AI maturity model is based on five core domains:

- **Strategy**: The strategy domain examines the state and nature of an organization plan of action and road map to support AI.
- **Organization**: This domain examines how a company is culturally and organizationally ready to support AI and its effects on business transformation.

- **Data**: This domain assesses the state and availability of data assets and its analytics capabilities, as these are crucial for a successful AI deployment
- **Technology**: This domain explores and assesses the different AI technologies and capabilities being leveraged by the company, and how it has been implementing AI solutions.
- **Operations**: This domain assesses where and how companies are implementing AI across four core operational elements: customer support, sales and marketing engagement, networks, and fraud detection management. The associated questions explore a range of potential use case scenarios, in both a B2C and B2B context.

In this study, four core phases of AI maturity are identified: *AI Novice*, *AI Ready*, *AI Proficient*, and *AI Advanced*. A corresponding assessment model identifying the AI development phase has been designed and the AI maturity can be aligned with the four core developmental phases as follows (Fig. 3):

- *AI Novice*: no proactive steps on the AI journey taken, at best is in assessment mode
- *AI ready*: sufficient preparation in terms of strategy, organizational set-up and data availability to implement AI
- *AI proficient*: reasonable degree of practical experience and understanding of how to move forward with AI, but with some gaps and limitations
- *AI advanced*: good level of AI expertise and experience, with a proven track record across a range of use cases

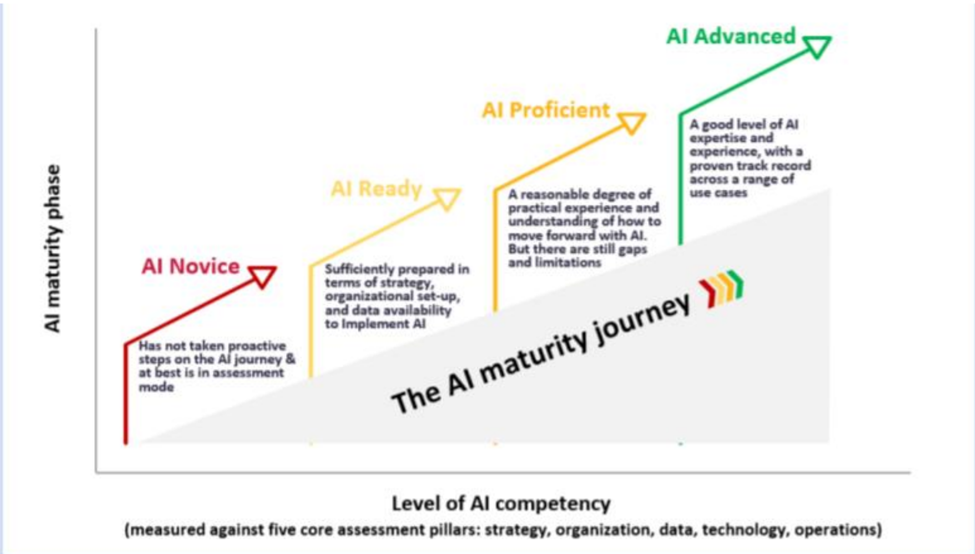

Figure 2. The AI maturity journey (Pringle and Zoller (Ovum), 2018)

Arunachalam et al, (2018) adopt a systematic literature review approach to understand multiple dimensions of Big Data Analytics (BDA) capabilities in supply chain. Through a structured search of literature conducted between 2008 and 2016 with appropriate key words, 82 peer-reviewed journal papers and 13 maturity models are selected, to analyse and define key BDA capabilities and maturity model specific to the supply chain context. The stages are identified as follows (Figure 2)

- At the *incognizant stage*, firms would lack knowledge about BDA and its benefits.
- At *initiation stage*, firms are aware of BDA and considering it for leveraging but have not implemented it. Organisations that are categorised into incognizant and initiation stages are presumably Data Poor and Information Poor, as the level of BDA capabilities will be low.
- Organisations in *adoption stage* (second and third quadrant) are aware of BDA technology, and involved in the process of adopting it. However, depending on the nature of capabilities they currently possess, an organisation in adoption stage can further be categorised into:
    - Organisation who possess a high level of Data Generation and Data Integration and Management Capabilities but not Advanced Analytics capabilities as Data Rich and Information Poor (DRIP)
    - Organisations that have leveraged some forms of analytics capabilities, but not collecting and integrating data from internal and external sources to the fullest.
- Organisations that possess a high level of all key BDA capabilities and fully integrate their business processes are at the stage of *routinisation*. These organisations will be the leaders in BDA practice and are certainly Data Rich and Information Rich (DRIR). Overall, assimilation of BDA capabilities can positively influence supply chain performance, but it requires commitment from top management.

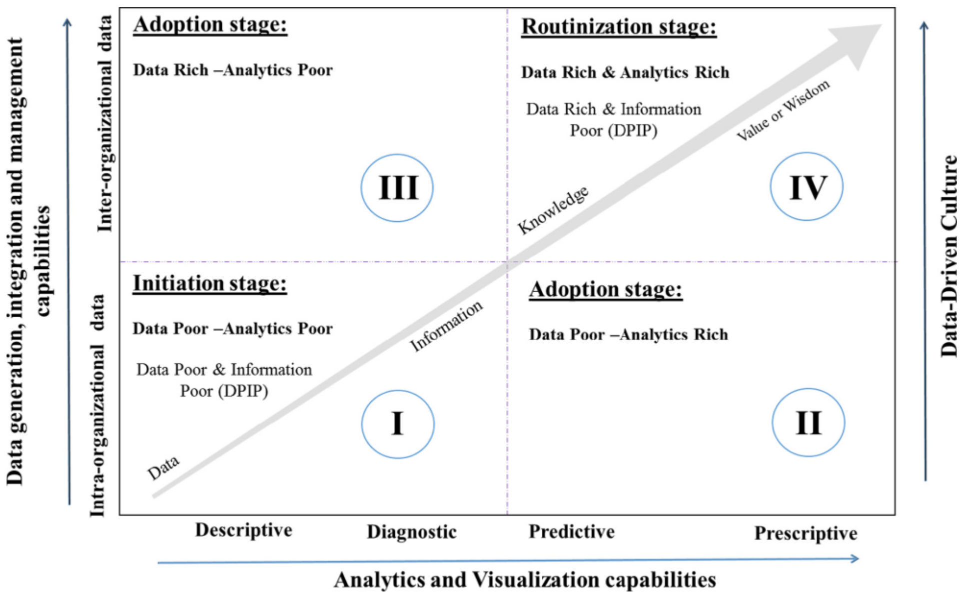

Figure 3. BDA capabilities maturity stages for the supply chain (Arunachalam et al, (2018))

Five domains related to big data capabilities have been identified as follows:

- **Data Generation capability**.
- **Data integration and management capabilities**.
- **Advanced capabilities**.

- **Data Visualisation capability**.
- **Data-driven culture**.

Alsheibani et al, (2019) develops an AI MLA model at the level of organisations. The results provide organisations with insights into the successful evolution and adoption of AI. Four domains have been identified:

- **AI functions**: it refers to the tools and technologies that are required to handling AI at scale
- **Data structure**: it refers to containing both the amount and structure of the data to get AI systems to work by enabling high-velocity capture, discovery or analysis.
- **People**: it refers to all those individuals within an organisation dedicated to creating artificial intelligence technologies.
- **Organisational:** it describes business characteristics and resources that might influence AI process such as firm size, managerial structure, decision-making and communication.

The model is based on 5 stages: initial, assessing, determined, managed, optimise

- *Level 1- Initial*. There is a lack of organisational knowledge. AI responsibilities are decentralised and have no dedicated unit for AI. It is essentially used by individual's function or team without the clear awareness of the organisation about the actual usage and it cannot be sufficiently measured and controlled by the organisational IT. Therefore, there is no AI-related governance or regular principles of operation which are extended to AI services by the users themselves
- *Level 2- Assessing*. The capability is well-developed, and the organisation has decided to move forward with AI application. The AI substructure is already functioning centrally and basic capabilities such as ad hoc analyses are provided. However, decentralised solutions still exist, and the organisation is faced with AI restriction issues.
- *Level 3- Determined*. The organisation becomes more conscious of inherent risks and opportunities for AI focusing on technology and tools. The organisation has standard operating procedures that cover AI scenarios. This level has strong top management which influences the challenge of aligning the AI with organisational goals; IT capabilities can be addressed.
- *Level 4- Managed*. Organisation capability is very well developed. In terms of achieving the primary goal for this stage there is a well-defined value to support and full top management support. Additionally, appropriate data science exists to make critical business decisions using AI.
- *Level 5- Optimised*. Responsibilities and accountability are clearly defined within each AI project. Data structure is flexible and pro-active to achieve business impact.

The maturity explanation of the domains in each stage is depicted in Table 2.

level	AI functions	Data structure	People	Organisation
Level 1 Initial	Very limited or no AI function exists and has no plans	Regular data structure; no data exists to train AI	Regular IT skills; Organisations lack the skills to evaluate, build and deploy AI solutions	No business case related to AI; existing structure are used informally
Level 2 Assessing	Discovery AI Technology	Integration of current usage of AI into data required to train AI	AI related training; Assessment of existing infrastructure with regard AI	Organisation initial AI strategy; for each AI application, have defined a value proportion
Level 3 Determined	AI project is at an advanced stage; determination of infrastructure needed to further implement AI	Custom AI data are introduced; data standardised are exist	Active management support; resources are provided, AI related employees training	Organisation has standard operating procedures that cover AI scenarios; change management is introduced
Level 4 Managed	AI process are defined throughout the organisations	Appropriate data science exists to make critical business decisions using AI	AI is being fully realised as employees' productivity	There is a well-defined value to support and full top management support
Level 5 Optimise	Full AI infrastructure adoption and standardisation	Proactive data analysis; Data is available in real time	Employees are engaged; centralised leadership	Role, responsibilities and accountability are clearly defined within each AI project; AI culture

Table 2. Maturity stages description in different domains (Alsheibani et al, (2019))

In Gentsch (2019), five domains have been selected, namely strategy, people, decisions, data and analytics. Figure 4 represents an overview of the five domains analysed with respect to the four algorithmic maturity levels. Data, algorithms and AI do not play a business-critical role when it comes to the n*on-algorithmic enterprise*. The topics are ascribed rather an operative and transactional significance. The strategy and organization are rather classical and less analytical and data driven.

Upon the transition to a *semi-automated* enterprise, the crucial value of algorithmic and AI is increasingly recognised. Accordingly, there are corresponding data and analytics structures. Characteristic is the increased degree of automation of data collection and analysis as well as the decision-making and implementation. This is made possible by a holistic integration of data sources, analyses and process chains. Data, analytics and AI facilitate the creation and implementation of new business processes and models in this maturity level. The data- and analytics-driven real-time company obtains systematic competitive advantages this way.

Whilst with the *automated enterprise* the approaches of narrow AI are applied, the *super intelligence enterprise* concludes the potential of autonomy and self-learning of companies by way of general and super intelligence. This scenario currently appearing to be hardly realistic has two types of manifestation.

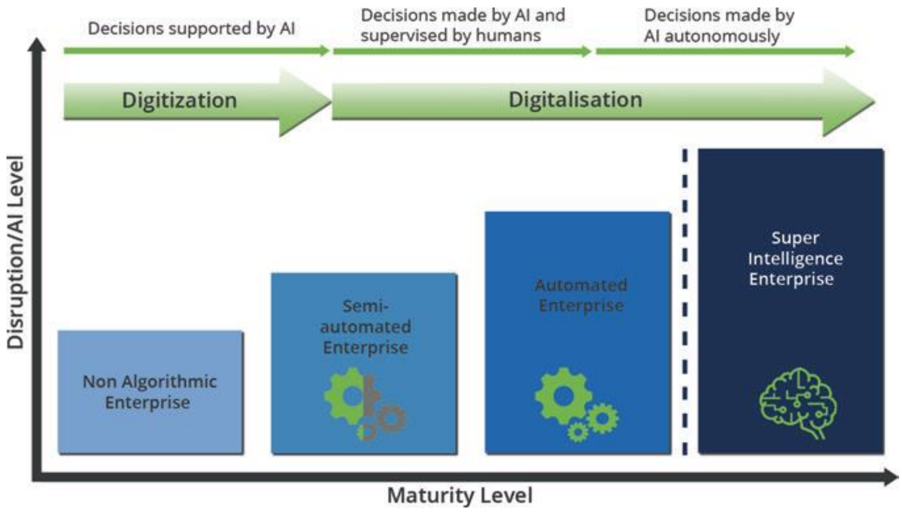

Figure 4 Algorithmic maturity levels

Element AI, (2020) catalogues five key dimensions that must be aligned to create and scale business impact with AI, namely Strategy, Data, Technology, People and Governance.

- **Strategy**: The plan of action for achieving the desired level of AI maturity in the organization.
- **Data:** The data required to support specific AI techniques defined by the AI strategy.
- **Technology:** The technical infrastructure and tools needed to train, deliver and manage AI models across their lifecycle.
- **People**: The leadership practices as well as roles, skills and performance measures required for people to successfully build and/or work with AI.
- **Governance**: The policies, processes and relevant technology components required to ensure safe, reliable, accountable and trustworthy AI solutions.

It also explains how these dimensions define an organization's maturity across five stages: Exploring, Experimenting, Formalizing, Optimizing and Transforming.

- *Exploring* organizations must spend time understanding what AI can really do and how it could be of value for them.
- *Experimenting* organizations find out what will actually work and at what cost.
- *Formalizing* organizations are putting their first models into production with clear performance metrics, and typically, they use this process to drive additional investments.
- *Optimizing* organizations are focused on building out their ability to select, deploy and manage running AI solutions in production.
- *Transforming* organizations are using AI to push the boundaries of the technology and their own strategy.

Airline network planning is a business process which relies heavily on information systems. Traditionally, IT systems have been used to perform mathematical optimizations of the airline network (Goedeking, 2010). To leverage the new big data opportunity, both business processes and the corresponding IT systems face a significant transformation. To this aim, Hausladen &

Schosser (2020) develop a Model for big data analytics in airline network planning which is capable to assess strategic, organizational and technological domains.

Four domains (with two sub domains) have been identified in the process of MLA model design:

- **Strategic alignment:**
  - The sub-domain **strategy** refers to the existence of a strategy for big data and network planning management, the alignment between these two strategies and the existence of financial resources to implement the strategies
  - **Culture** sub-domain refers to the need for an executive sponsorship of big data initiatives, the need for recognition of created business value and the existence of positive attitude towards big data
- **Organization:**
  - **Organizational structure** refers to roles & responsibilities and clearly assigned mandates to implement big data analytics initiatives. The transparency on governance structures is an additional maturity measure
  - **Employee skills** refers to the skill level of NPM department, the formal development of skills for big data and the hiring of external talent
- **Data:**
  - **Data sources** refers to the richness of available data and to data proprieties as availability, transparency, etc.
  - **Data management** focuses on the process of data, including extracting, processing, and analysing data; it can be distinguished between data storage and data quality assurance
- **Information technology:**
  - **IT architecture** refers to different aspects such as the integration of data source and the architecture transparency and flexibility
  - **IT tools** refers to the analytics capabilities, effectiveness of decision support system and the degree of automation

This Model is based on five stages (levels 1 to level 5).

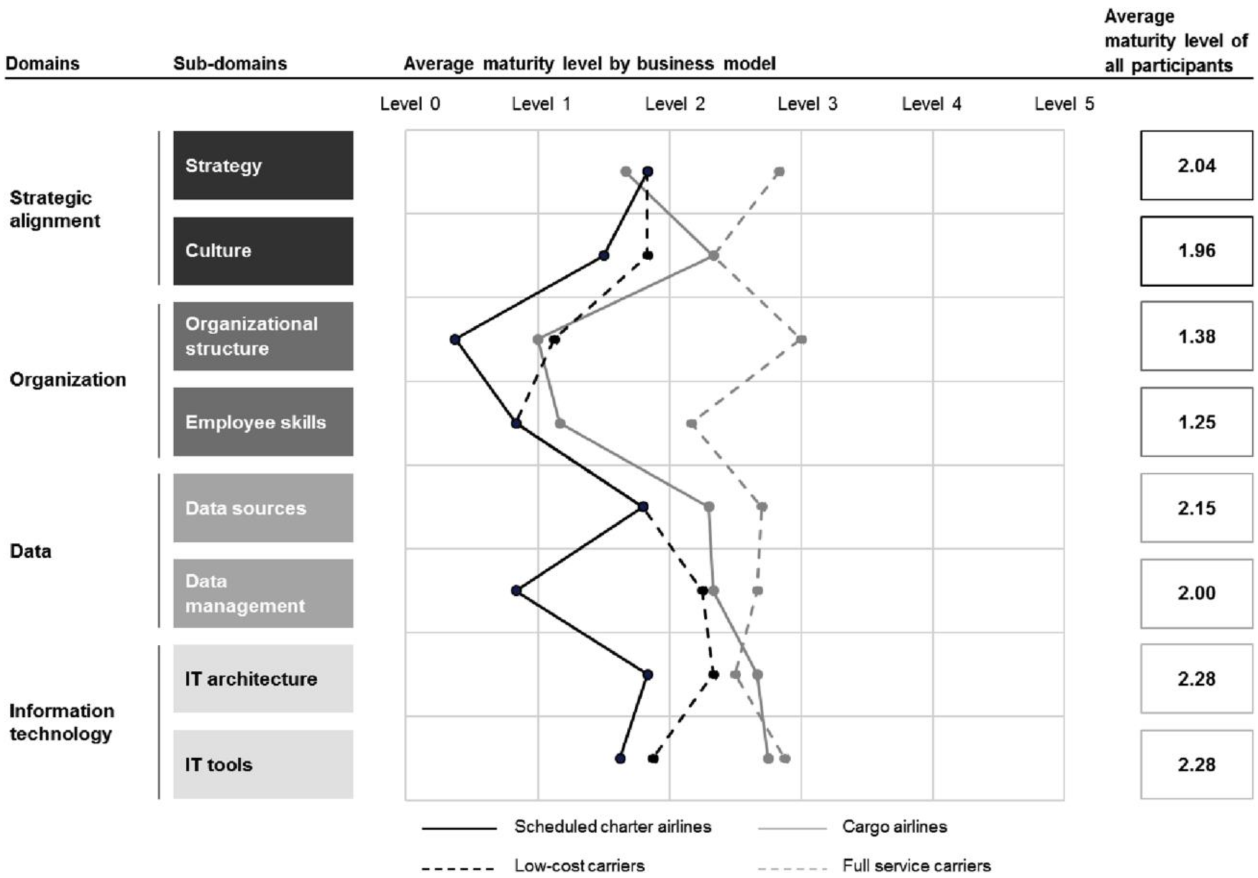

Figure 5. Maturity patterns in the airline companies (Hausladen & Schosser (2020))

To aid organizations wherever they are on their AI journeys, Intel has created a Readiness Model to help decision makers understand where to prioritize efforts. INTEL provides guidance on how to judge an organization's ability and readiness to use AI to generate business value and includes a list of questions which can be used to guide self-assessment activities.

In the framework proposed by INTEL, the companies' progress to the next stage or to ongoing success depends on having the right elements in place across skills and resources, infrastructure and technology, processes, and models. Three areas/domains have been identified: (i) foundational readiness is the first step, but the success of AI depends on (ii) operational readiness, and then how receptive the business is to AI – i.e. (iii) transformational readiness:

- **Foundational readiness**
- **Operational readiness**
- **Transformational readiness**

The model proposes 3 level of maturity:

- *Using AI for the first time*
    - An organization with existing pools of data can benefit from the use of AI.
    - An organization is running a workload in a traditional environment, and wants to apply AI or machine learning to explore opportunities for optimization
    - An organization has been researching the potential of AI
- *Scaling up use of AI*
    - An organization may have developed a proof of concept AI solution running on a workstation or a single device.

  - An organization has developed a 'home-grown' solution, and is now looking to use industry standard infrastructure and/or software
- *Broadening out use of AI*
  - An organization may be using AI successfully in a line of business and is now looking to expand.
  - An organization is successfully using AI to learn from and interpret data, and now wants to extend into inference-based maintenance and updates to models.

4.3 THE ROLE OF ELSI PARAMETERS

Many of these MLA models evaluate the ethical impact indirectly, investigating transparency of data management, privacy management, etc. Little emphasis is given to legal and social issues. In this section we summarize some important documents developed in Europe concerning these topics to have a basis for AI-CUBE model.

Trustworthy AI has **three components**, which should be met throughout the system's entire life cycle (European Commission, 2019) (Figure 6). It should be:

2. **lawful**, complying with all applicable laws and regulations
3. **ethical**, ensuring adherence to ethical principles and values
4. **robust**, both from a technical and social perspective since, even with good intentions, AI systems can cause unintentional harm

The development, deployment and use of AI systems should meet the seven key requirements for Trustworthy AI: (1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, non-discrimination and fairness, (6) environmental and societal well-being and (7) accountability.

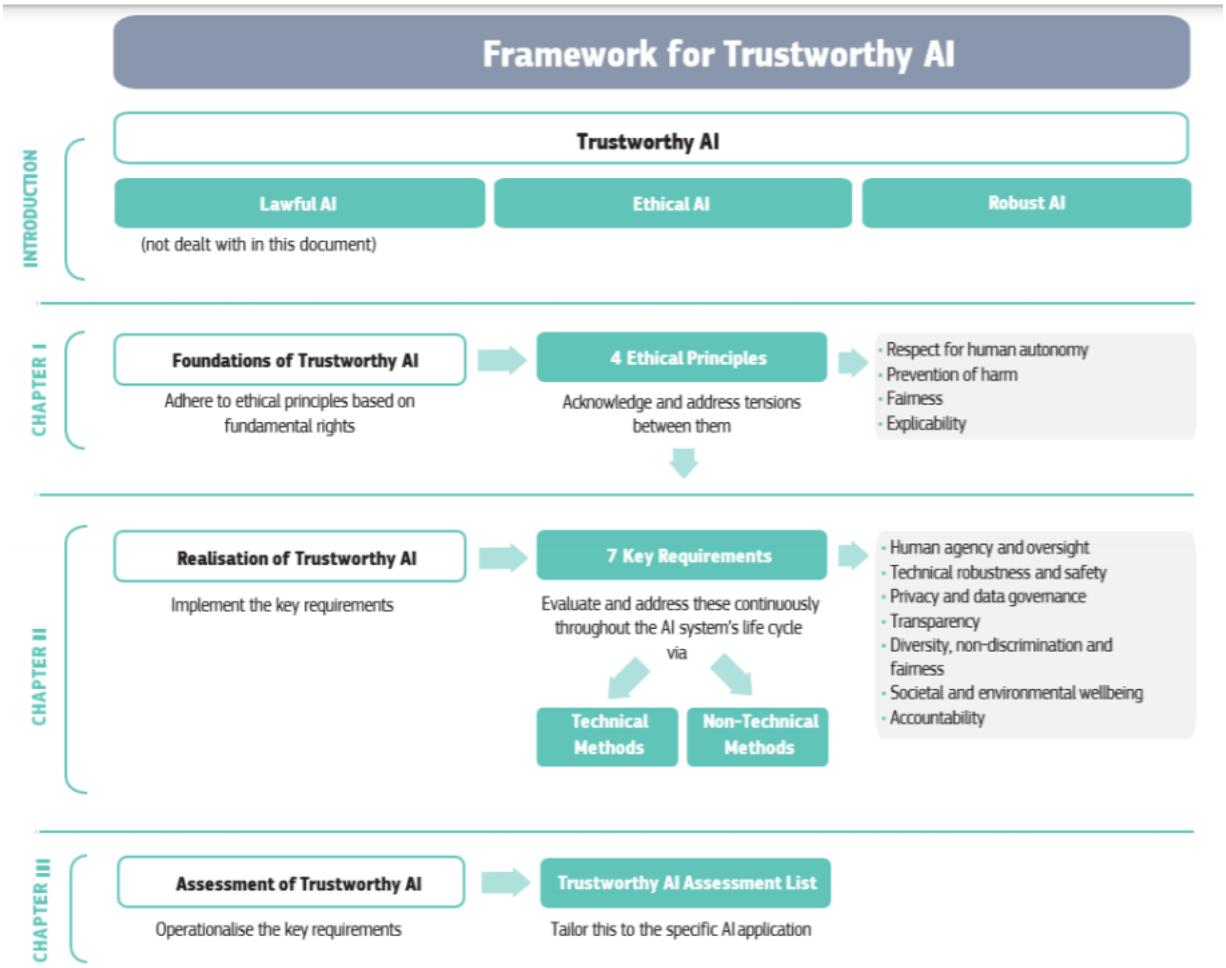

Figure 6. Framework for trustworthy AI (European Commission, 2019)

AI systems should improve individual and collective wellbeing. European Commission (2019) lists **four ethical principles**, rooted in fundamental rights, which must be respected in order to ensure that AI systems are developed, deployed and used in a trustworthy manner. They are specified as **ethical imperatives** that AI practitioners should always strive to adhere to them. These are the principles of:

- **Respect for human autonomy**
- **Prevention of harm**
- **Fairness**
- **Explicability**

The development, deployment and use of AI systems should meet the **seven key requirements** for Trustworthy AI:

1. **Human agency and oversight**
2. **Technical robustness and safety**
3. **Privacy and data governance**
4. **Transparency** (*including traceability, explainability and communication)*
5. **Diversity, non-discrimination and fairness** *(including avoidance of unfair bias, stakeholder participation, accessibility and universal design)*

6. **Societal and environmental well-being** (*including sustainable and environmentally friendly AI, social impact, society and democracy)*
7. **Accountability** *(including auditability*, *minimisation and reporting of negative impacts*, *trade off*, *redress*)

The 'Regulation on ethical principles for the development, deployment and use of artificial intelligence, robotics and related technologies' (European Parliament, 2020) builds on the following principles:

- human-centric, human-made and human-controlled artificial intelligence, robotics and related technologies;
- mandatory compliance assessment of high-risk artificial intelligence, robotics and related technologies;
- safety, transparency and accountability;
- safeguards and remedies against bias and discrimination;
- right to redress;
- social responsibility and gender equality in artificial intelligence, robotics and related technologies;
- environmentally sustainable artificial intelligence, robotics and related technologies;
- respect for privacy and limitations on the use of biometric recognition;
- good governance relating to artificial intelligence, robotics and related technologies, including the data used or produced by such technologies.

The development, deployment and use of artificial intelligence, robotics and related technologies, including the software, algorithms and data used or produced by such technologies, should **complement human capabilities**, not substitute them, and ensure that their execution does not run against the best interests of citizens (European Parliament, 2020) and in particular:

- Decisions made or informed by artificial intelligence, robotics and related technologies should remain subject to meaningful human review, judgment, intervention and control.
- Any artificial intelligence, robotics and related technologies, including software, algorithms and data used or produced by such technologies, should be developed, deployed and used in the Union:
    - in a human-centric manner and based on the principles of human autonomy and human safety in accordance with Union law;
    - in full respect of fundamental rights such as human dignity, right to liberty and security and right to the integrity of the person;
    - in a safe, transparent and accountable manner in accordance with the safety features of robustness, resilience, security, accuracy and error identification, explainability, interpretability, auditability, transparency and identifiability.

4.4 SYNTHESIS AND OUTCOMES OF THE LITERATURE ANALYSIS

Considering the literature described in the previous sub-sections, Table 3 depicts a general overview of the application fields, sectors, and assessment levels. While some scientific works are related to the theoretical analysis and conceptualisation of different maturity levels in different areas related to a specific industrial sector, some other consultancy and scientific works develop and validate an MLA framework of different areas in a sector via the implementation of different methods like surveys or questionnaires for experts in the field under analysis.

The most important gaps identified in the above analysis are:

- Process industry has never been considered as a sector *per se* and a comprehensive framework dedicated to this sector is missing.
- MLA frameworks are available for AI or BD in separate approaches, and in some cases data management is considered when treating AI
- MLA frameworks do not consider multi-actors approaches to have the perspective of different type of stakeholders (i.e. users and providers of AI/BD).

Table 3. Literature summary on the applications and assessment

Reference	AI/BD focus	Source	Application sector
Element AI, (2020)	AI	Consultancy company	Banking&Finance Professional services Insurance Manufacturing Health &pharma Retail
Comuzzi and Patel, (2016)	BD	Scientific paper	Marketing and advertising Financial services Digital content delivery
Pringle and Zoller (Ovum), (2018)	AI	Consultancy company	communication and media service provider (CSP)
Hausladen & Schosser (2020)	BD	Scientific paper	Airline companies
Alsheibani et al, (2019)	AI	Scientific paper	Australian SMEs
Gentsch (2019)	AI	Scientific paper	N/A
Arunachalam et al, (2018)	BD	Scientific paper	N/A
Defize (Deloitte), (2020)	AI	Consultancy company	N/A
INTEL	AI	Consultancy company	N/A

Table 4 summarizes the categories used in the mentioned studies, from which emerges the importance of assessing the strategic alignment and organisational aspects in the AI/BD management. This emphasises the importance of a cultural and managerial approach for the AI/BD applications. In addition, the role of data and technology is fundamental in the maturity identification. Most of the MLA frameworks consider various aspects of the data maturity.

Table 4. Literature overview for the domains analysed for maturity level identification

	Domains							
Reference	**Strategy**	**People**	**Organisation**	**Governance**	**Data**	**Technology**	**Operation**	**AI functions / Analytics**
Element AI, 2020	✓	✓		✓	✓	✓		
Comuzzi and Patel, 2016	✓		✓	✓	✓	✓		
Pringle and Zoller (Ovum), 2018	✓		✓		✓	✓	✓	
Hausladen & Schosser (2020)	✓		✓		✓	✓		
Alsheibani et al, 2019		✓	✓		✓			✓
Gentsch, P. (2019).	✓	✓	✓	✓	✓			✓
Intel				✓		✓	✓	
Arunachalam et al, 2018					✓			
Defize (deloitte), 2020					✓			

Regarding the levels of maturity for AI/BD, the literature identifies between 4 and 6 levels (Table 5), usually ranging from the worst one with limited AI/BD application and knowledge inside the company, to the level that considers the company/sector as the most advanced in AI/BD in application and knowledge among the people. The choice of the number of stages depends on the level of maturity that is necessary to define for a certain research area and the level of granularity to be given to the analysis.

Table 5. Literature overview for the levels of the maturity in AI/BD

stages	Element AI, 2020	Comuzzi and Patel, 2016	Pringle and Zoller (Ovum), 2018	Hausladen & Schosser (2020)	Alsheibani et al, 2019	Gentsch, P. (2019).	Intel	Arunachalam et al, 2018	Defize (deloitte), 2020	
1	Exploring	level 1	AI Novice	level 0	initial	non algorithmic enterprise	using AI for the first time	incognizant stage	Initial	experimental
2	Experimenting	level 2	AI ready	level 1	assesing	semi-autometed enterprise	scaling uop use of AI	initiation stage	managed	ready
3	Formalizing	level 3	AI proficient	level 2	determined	automated enterprise	broadening out use of AI	adoption stage	defined	semi-automated
4	Optimizing	level 4	AI advanced	level 3	managed	super-intelligent enterprise		routinisation stage	quantitative ly managed	automated
5	Transforming	level 5		level 4	optimise				optimized	advanced
6				level 5						

5. Design of the MLA Framework for AI-CUBE

Considering the focus of AI-CUBE and compared to the studies analysed above, we have designed a customized MLA framework for the process industry with a comprehensive approach of mapping AI and BD technologies within the processes, analysing the interplay between each technology and each process. As underlined, the MLA models available in literature don't cover the full spectrum of our requirements and there are some gaps to be fulfilled. The proposed MLA framework can be used to:

1. assess the as-is situation of the organization/process;
2. approach maturity improvement in order to positively affect business value;
3. enable benchmarking across companies; in particular, a model of this nature would be able to compare similar practices across organizations.

Another contribution of the proposed MLA framework compared to the literature is the multi-level approach, where the maturity is classified in two levels: company and technology. In particular, the results of the survey can identify the maturity level based on the technological questions, while the effect of the general company approach through strategy, organization, and people is also taken into consideration. This approach helps bridging the gap in the theory of maturity models and leveraging AI/BD solutions.

5.1 THE AI-CUBE MLA CONCEPTUAL FRAMEWORK

The AI-CUBE MLA conceptual framework is grounded on the following content:

- literature analysed in the previous sections to gather the most important domains for maturity analysis in case of digital technologies like AI and BD;
- analysis of the process industry in WP1 of AI-CUBE project, where most important processes, and AI/BD technologies have been classified for further analysis;
- position paper from SPIRE related to AI, from where some important barriers to AI implementations like organisation, training etc are depicted.

Given these inputs, the AI-CUBE consortium decided to consider the following dimensions for the AI-CUBE MLA framework:

- ***Strategy:*** it concerns the strategic alignment of a company towards the AI/BD applications. A winning company is the one which has a clear strategy, integrated with the corporate level, and committed by the top management. To this end, companies' culture from the top management to employees to AI/BD needs to be evaluated. Furthermore, AI/BD for successful companies are considered as a competitive advantage, which brings the added value and is aligned with the ethical, legal, and social issues. The maturity level will be evaluated based on:
    - **company strategic alignment** with the AI/BD applications, i.e. alignment of AI/BD with other business goals and degree of relation of data to the business goals.
    - **cultural attitude** of the company towards AI/BD, i.e. interest in AI/BD initiatives, data-driven culture, and the approach to change management

- contribution of AI/BD applications to create **added value** in a company, i.e. competitive advantage deriving from AI/BD applications for the company and stakeholders
- awareness of **ELSI** (Ethical, Legal, Social Issues) strategies
- degree of **awareness and monitoring strategies** for the ELSI and their alignment to company's strategy

- ***Organisation:*** it concerns the role of AI/BD experts and AI/BD governance capabilities within the company and its organisational structure. These aspects can affect the financial status and companies' capabilities to handle their AI/BD applications internally. Winning companies have centralised AI/BD responsibilities, utilise the expertise of data scientists as a formal organisational role, and benefit from the full management support. The maturity level will be evaluated based on:

  - **AI/BD governance** in a company, i.e. transparency and incorporation of governance roles (CDO/CTO) at corporate level and their association to company KPIs.
  - **AI/BD responsibilities** are tied to the organisational structure of a company, i.e. AI/BD responsibilities centralisation, existence of appropriate data scientists, and top management support.
  - **financial and economic budget** handled specifically for AI/BD development and monitoring, i.e. dedication of financial resources to AI/BD projects, economic evaluations, and the level of funding for the AI/BD-related sectors.
  - **privacy management strategy**, with respect to the governance of data access, privacy protection, and regulation alignments.
  - development and maintenance of the **AI/BD projects** managed internally or outsourced

- ***People:*** it focuses on the role and approach of each employee towards digitalisation. People inside a company need to be trained to align to the AI/BD objectives of the company. AI/BD experts should have a fruitful collaboration with the other employees, so that they are aware of the initiatives affecting their roles.
  - **Employees engaged** in the AI/BD initiatives, i.e. their skills level and ability to develop AI/BD projects and solve relevant problems, and top management support
  - **AI/BD skill development** associated within the corporate and functional levels
  - **AI/BD responsibilities** between corporate level and functions are clearly defined for AI/BD management
  - **AI/BD skill level** in the company, i.e. staff awareness and alignment with the fast-paced technological evolution
  - **Collaboration** between Digital Experts & other Employees (traditional works) effective

- ***Technology:*** it concerns the availability of AI/BD technologies within the different processes of a company, it is therefore crucial to evaluate the maturity of each technology. This dimension encompasses the MLA analysis of the technology and process axis of the Cube and it is related to:
  - Level of usage and integration of AI/BD within the different steps of each process
  - Human interaction in AI/BD applications
  - Risk-averse strategies and level of flexibility to unforeseen situations
  - degree of decision-support by AI/BD at process level

- *Data:*
  - Richness of available data concerning internal and external data
  - Transparency on available data of internal and external data
  - Frequency of data updates related to real time data gathering
  - Data quality measured as completeness of data collected in terms of frequency, missing data, formatting, unique identification of source
  - Capabilities to process unstructured data by AI/BD

5.2 IDENTIFICATION OF MATURITY LEVELS IN AI-CUBE MLA FRAMEWORK

Based on the maturity levels proposed in the literature in Section 4.1, we have chosen to structure the possible answers on 4 levels, as an intermediate level between min and max number of levels (3 to 6) proposed by other MLA models and because three levels of maturity will be too little to differentiate the positions of companies in implementing AI/BD and 5 and 6 will give too much detail that is not necessary at this stage of the project. In particular, the levels are characterized as follows:

Level 1 - ***little or no adoption of the practice***: companies have little knowledge of the topic and the practice is not applied in the companies.

Level 2 - ***experimenting the practice with limited use***: companies are starting to experiment and test a certain practice along their processes.

Level 3 - ***on the way of formalizing and adopting the practice***: companies are at a good stage of implementation of a practice with high impact on the processes.

Level 4 - ***full adoption and optimization of the practice***: companies that are champions of a practice which is well established and recognised as important for their processes.

In the following table we summarize the MLA framework levels and the domains described in the previous section is represented in Table 6, where the framework considers the overall performance of a process industry towards AI/BD. Table 7 represents the MLA framework for the technological and process aspects of the company. Therefore, these aspects will be considered in evaluating the maturity of each technology and process in the CUBE.

Table 6 MLA framework at company level

Strategy	Level 1	Level 2	Level 3	Level 4
Strategic alignment towards AI/BD	No specific strategy for AI/BD; data is not regarded as critical to success no alignment of the AI/BD strategy with overall business goals	Rudimentary AI/BD strategy; Data is regarded as business-relevant Partial alignment of the AI/BD strategy with business goals	Decided AI/BD strategy; Data as value drivers and competitive advantage. full Alignment of the AI/BD strategy with business goals	Strategy related to resources; data and analytics are the subject of planning and execution process and are part of the overall company strategy
Cultural attitude towards AI/BD	No interest in AI/BD use; initiatives usually disregarded; change	There is the interest in AI/BD; but initiatives are difficult to be implemented and are	In addition to the interest in the initiatives, there is a common understanding among	AI/BD initiative are welcomed by the managers and employees; usually

	management is not introduced	unsuccessful because of a common understanding of change is missing	the employees of AI/BD change management; company approaches data-driven culture	initiative by sponsors are welcomed and successfully implemented; there is trust in the outcome of the initiatives
Business opportunity	AI/BD don't add value to the business; It seems that the company cannot obtain a competitive advantage by its AI/BD applications	Although some AI/BD applications are understood and appreciated, the added value is negligible	AI/BD applications are considered as one of the value-added strategies of the company; company obtains a competitive advantage	AI/BD is a core value-added activity and competitive advantage for the company
ELSI awareness and monitoring	Company is not aware of the ethical, legal and social issues of the AI/BD and doesn't have a strategy to monitor this dimension	Company knows there can be issues to control ethical, legal and social issues of the AI/BD but do not have any strategy to control	Company is fully aware of the need to control ethical, legal and social issues of the AI/BD and is starting to implement some strategies	The control of the ethical, legal and social issues of the AI/BD are part of the company strategy
ELSI (Ethical, Legal, Social Issues) strategies	There is no ELSI strategy in the company	There is ELSI strategy in the company, but not clearly defined and it may not be aligned with the objectives in different functions of the company	ELSI strategies are clearly defined and supported by management. However, it may not be coherent with corporate strategies or objectives in different functions in the company	ELSI strategies are transparently defined and communicated. All the ELSI strategical aspects are adapted to the regulations and verified for its compatibility of corporate strategies
Organisation	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Governance	AI/BD governance on corporate level not transparently defined	AI/BD governance on corporate level unclear informally existing	AI/BD governance on corporate level defined, but not fully transparent to all functions; AI/BD governance roles at corporate level incorporated in the role of the CDO/CTO	AI/BD governance on corporate level fully transparent and known to employees; AI/BD performance measured and reported to top management as one of the KPIs in the company
Organisational structure	AI responsibilities are decentralised and have no dedicated unit for AI. It is essentially used by individual's function or team without clear awareness of the organisation about the actual usage; it cannot be sufficiently measured and controlled by the organisational IT	The AI substructure is already functioning centrally and basic capabilities such as *ad hoc* analyses are provided. However, decentralised responsibilities still exist	Strong top management which influences the challenge of aligning the AI/BD with organisational goals; IT capabilities can be addressed through integrated responsibilities	There is full top management support; appropriate data scientists exist to make critical business decisions using AI/BD; Responsibilities and accountability are clearly defined within each AI /BD project
Financial and economic strategies	No financial resource dedicated to AI/BD development and monitoring; No economic evaluation of the profitability of AI/BD initiatives	Initial economic evaluations justifying the profitability of AI/BD applications; financial resources are not enough to implement the strategies	Complete feasibility study of the economic aspects of AI/BD applications; applications proved to be profitable are partially funded for implementation and monitoring	As a result of the feasibility study for discovering the profitable applications of AI/BD, all the interested applications for implementation and monitoring are fully funded
Privacy	No governance for data access, privacy protection, and regulation alignments	Basic level for data access, privacy protection, and regulation alignments	The data access, privacy protection, and regulation alignments are partially implemented	The data access, privacy protection, and regulation alignments are fully respected
Development and maintenance of the AI/BD	Completely outsourced (development, installation, customisation of functionalities and maintenance)	Partially outsourced (some modules are outsourced some are developed internally)	Partially outsourced (development, installation and maintenance). Customisation (i.e. integration and link to	Completely self-managed in the company

			other sw in the company) held in the company	
People	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Employees engagement	Regular IT skills; Organisations lack the skills to evaluate, build and deploy AI/BD solutions	AI/BD related training; Assessment of existing infrastructure with regard to AI/BD	Active management support; resources are provided, AI/BD related employees training	AI/BD is being fully realised as employees' productivity; Employees are engaged; centralised leadership
AI/BD skill development	No formal development of AI/BD skills in the organization	Basic development of AI/BD skills (e.g., user training for BD tools)	Broad formal AI/BD skill development	AI/BD skills essential part development (also reflected in job descriptions)
Definition of responsibilities between corporate level and functions	Responsibilities of AI/BD between corporate and functional levels is unclear	Responsibilities of AI/BD between corporate and functional levels is not well defined and sometimes unclear	Responsibilities of AI/BD between corporate and functional level is defined, but remain sometimes unclear	Responsibilities on AI/BD between corporate and functional level is clearly defined
AI/BD skill level	Staff lack awareness of AI/BD	Staff have mainly a personal interest in AI/BD, but lack the required skills to track the fast-paced technological evolution	Individual experts develop deep knowledge on AI/BD tools and topics	All staff is fully engaged with AI/BD technology and tools
Effective Collaboration between Digital Experts & other Employees	There is no collaboration between digital experts and other employees. AI/BD projects are carried out by mere involvement of digital experts, without the collaboration of other employees	The collaboration between digital experts and other employees is limited to situations that require other employees' involvement. AI/BD projects are carried out only by digital experts	Employees are partially involved in AI/BD projects and are asked by digital experts for their feedback	Strong and effective collaboration between digital experts and other employees. Employees are always updated with the last digitalisation trend in the company and involved actively in the AI/BD projects. Digital experts consider their feedback as a precious for company's digital transformation

Table 7. MLA framework at technological and data level

Technology	Level 1	Level 2	Level 3	Level 4
Level of usage and integration of AI/BD	Use of basic functionality of AI/BD for isolated steps of the process	Use of AI/BD for most steps of the process	Use of single application for all the process steps, but no integration with other applications	Use of all AI/BD based applications is integrated for the process steps
Human interaction in AI/BD applications	No design for human-in-the-loop AI/BD functions; employees interact with AI/BD when necessary and based on experience	No design for human-in-the-loop AI/BD functions; employees interact with AI/BD based on a preliminary evaluation based on experience and functions	There is a design and evaluation for human-in-the-loop AI/BD functions and employees are assigned based on this design	In addition to the design and evaluations for employees' interaction, AI/BD applications automatically schedule and update the necessary employee interactions and reviews
Risk-averse strategies and level of flexibility	No strategy for unforeseen situation, all algorithms rigidly defined; any flexibility carried out through human intervention and experience	There is a plan for unforeseen situations and employees are aware of intervention types; the algorithms are not fully aligned	Algorithms are capable to warn the users in case of unforeseen situation; employees are aware of their tasks; a mix of AI/BD and human interaction manages the risks	The risks are foreseen and algorithms alert the users; algorithms are flexible enough to manage the risks; employees have monitoring tasks
Degree of decision-support by	All decisions at process level are judgement-based, no support by AI/BD tools	Few decisions are AI/BD-evidence based, but most decisions are based on experience	Most decisions are evidence-based and grounded in data and decision makers are	All major decisions are evidence-based and grounded in data, and all decision makers are

AI/BD at process level		and individual judgement	trained sporadically to use and interpret data from AI/BD	trained to use and interpret data on a regular base
Data	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Richness of available data	Only internal controlling data used for AI/BD	Mostly internal data used, but not all information needs can be satisfied	Most information needs can be satisfied with either internal or external data	Large selection of internal and external data available to satisfy all information needs with best possible data
Transparency on available data	Basic transparency on data gathered	Satisfactory transparency on internal data	Full transparency on internal available data	Full transparency on internal and external available data
Frequency of data updates	No real-time data feeds (neither internally nor externally)	Real-time data feeds possible only for selected internal data (e.g., booking data)	Real-time data feeds possible only for all internal data	Real-time data feeds possible both for internal and external data
Data quality	Data quality is really poor in terms of frequency of collection, completeness of data, formatting, unique identification of source	Data quality is poor in terms of frequency of collection, completeness of data, formatting, unique identification of source	Data quality is good in terms of frequency of collection, completeness of data, formatting, unique identification of source	Data quality is really good in terms of frequency of collection, completeness of data, formatting, unique identification of source
Capabilities to process unstructured data	Unstructured data (text, video, audio) cannot be processed by AI/BD systems	AI/BD with capability to process certain forms of unstructured data (e.g., text analysis)	Capability to process most unstructured data (e.g., text analysis) necessary for the decision to be taken	Capability to process all forms of unstructured data (e.g., text analysis) necessary for the decision to be taken

5.3 THE AI-CUBE MLA TOOL

Given the AI-CUBE MLA conceptual framework described above, the next phase is related to the choice of the method to operationalize and, hence, put into practice the framework itself.

As for the methodology to be applied, we decided to proceed formalising a questionnaire for organisations' self-assessment. The use of a questionnaire allows to reach a wider number of respondents in many sectors of the process industry. Given the fact that we have to reach 8 sectors in the process industry and we would like to gather also the feedback form the AI/BD providers, associations, and service consultants we aim for a questionnaire based on the domains identified above.

The AI-CUBE project targets process industries, policymakers, consultants, associations, and service providers, as the project aims to provide better understanding of the digital technologies application to support their uptake across process industries. To achieve this understanding, we identified the following two categories of potential respondents to the AI-CUBE MLA questionnaire:

- **AI/BD users**: this category includes production unit and production plants of the process industry. The relevant employees will give feedback regarding their own processes and the application of AI/BD in their own company plants.
- **AI/BD providers**: this category includes software providers, system integrators, consultants, associations who have the knowledge and expertise related to AI/BD application in one or more than one process industries. Their feedback is targeted to understand the MLA of process industries from an external perspective and therefore, they will be asked to give their perception of companies from process industry in AI/BD projects.

In particular, as the MLA addresses both users and providers of AI/BD technologies, the answers given by the providers will be used as benchmark for the score of the user companies. This approach based on 2 types of respondents, allows to have the vision on the single company itself and on the system, where AI/BD users have their own perception of their own adoption of these technologies while AI/BD providers can offer an overview of the system.

The respondents will do a self-assessment since the questionnaire is structured in a simple way and it will be available as an online survey. Since it is important that we define a common terminology, they will be provided with a glossary with the AI-CUBE definitions for the AI/BD categories identified as well as a glossary for the processes identified in previous activities of the project (in annex 4 and 5).

The flow of questions is represented in the figure below. In particular, after the set of questions characterizing the respondent in an anonymous way, there are three levels of questions:

- questions related to the company and in particular the domains related to organisation, strategy, and people.
- questions to identify the technologies and processes in which the company applies AI /BD.
- for each technology claimed to be applied, the respondents are asked to evaluate the maturity, by answering the questions concerning technological aspects.

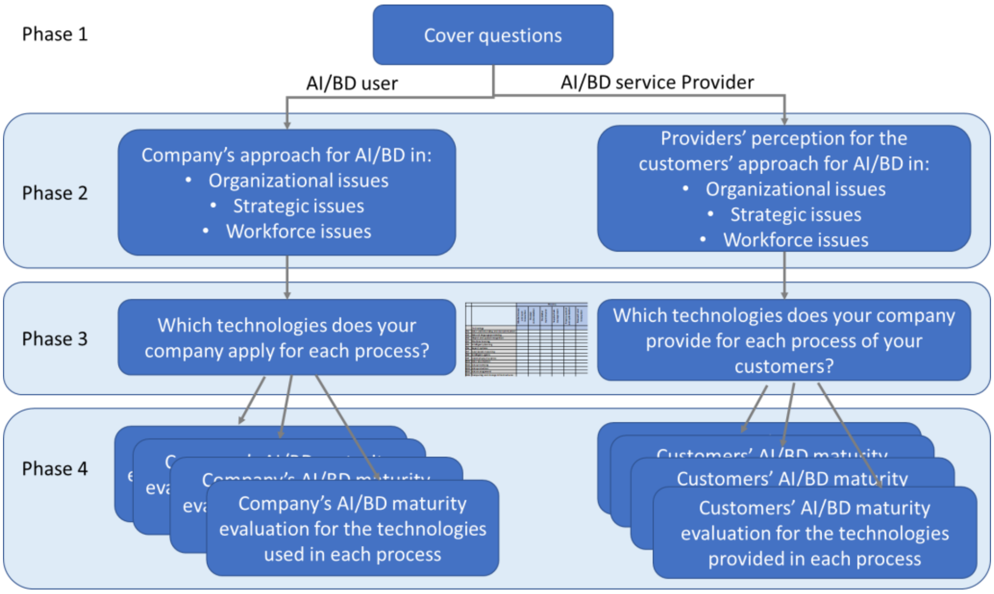

Figure 7. Flowchart for the survey design

The details of the questions are provided in the Annexes 1-2-3 to this deliverable.

5.4 SCORING SYSTEM FOR THE AI-CUBE MLA MODEL

Each respondent is asked to give a score from 1 to 4 to each question. The scores in each domain are aggregated and weighted to obtain one single score per each technology, per each process, per each company. This overall score represents the maturity of a company / sector in the application of a technology in a process.

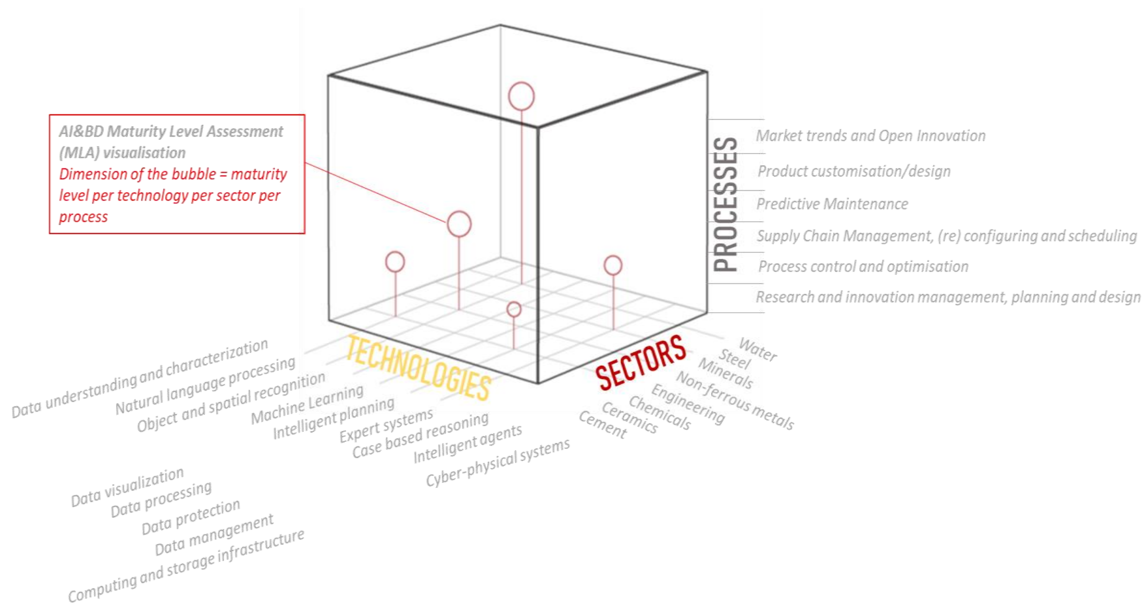

Figure 8. The CUBE

These aggregated scores will be used to populate the CUBE and the score will be reflected by the dimension of the bubble inside the cube in fig.8 and will represent the Technology Maturity level (TML); the bigger the bubble, the higher the score, hence the higher the TML of a specific technology in a certain process of a sector. The comparison between the bubbles will facilitate the benchmark of the SPIRE sectors.

Moreover, further analyses of the results based on the work in Arunachalam et al, (2018), as represented in fig. 8, will help to define a roadmap of development for the next years, as expected in activities in WP3 and WP4.

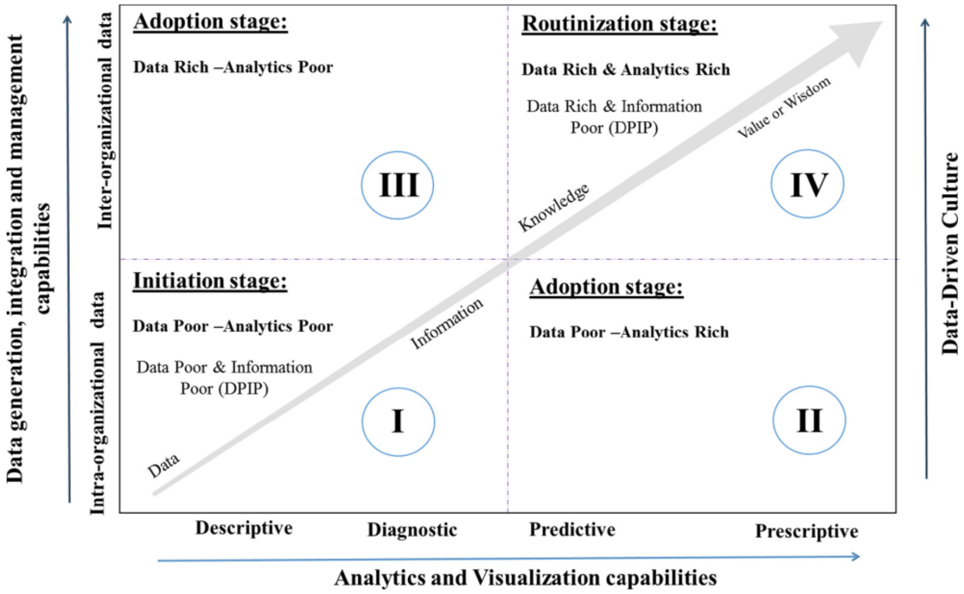

Figure 8. BDA capabilities maturity stages for the supply chain (Arunachalam et al, 2018)

6. Conclusions and Next Steps

In this deliverable we developed the framework to identify the maturity level of AI and BD technologies against the CUBE's pillars, along with a survey tool to gather data from AI/BD technology users and providers. Based on the analysis of the literature on the MLA models, and adapting the dimensions and elements of extant MLAs to the aims of the AI-CUBE project and the WP2 activities, the novel AI-CUBE MLA framework was described in this deliverable, defining a set of questions and a scoring system for the survey results.

With this comprehensive approach of aggregating AI and BD technologies with the processes, we can analyse the interplay between each technology and each process. Considering the focus of the project and compared to the similar studies, the MLA framework provides customized questions for the process industry; therefore, the results will provide insights to design tailored suggestions and identify potential gaps in the technological maturity levels for process industries.

Another novel contribution of the proposed MLA framework and related questionnaire is the multi-level approach, that drove the classification of the questions into two levels: company and technology. In particular, the results of the survey will identify the technological maturity level based on the technology-based questions, while the effect of the general company approach through question levels of strategy, organization, and people is also considered. This approach helps bridging the multi-level gap in the theory of MLA and leveraging AI/BD solutions.

By differentiating the targeted respondents into users and providers, the questionnaire aims at analysing the maturity level of AI/BD user industries, as well as providing a benchmarking framework through the providers' feedback to build the technology - sector - process/application in the CUBE. This approach helps testing and validating the results gathered from the single users and therefore, scaling up and broadening out the use of AI/BD initiatives.

To finalize the work conducted under T2.3, the questionnaire developed and included in Annex 1-2-3 to this deliverable, will be sent for testing and validation to selected experts in each of the AI-CUBE partner organisations to collect feedback that will be used in WP3 for the refinement of the questionnaire. The final version of the questionnaire will be transformed in an online survey to be sent to potential respondents identified through the stakeholder analysis run under WP2 (T2.1, D2.1).

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8. ANNEX 1 - THE QUESTIONNAIRE FOR THE MLA MODEL

Phase 1: Cover questions

This phase is dedicated to the general questions to identify the typology of the company and the responsibility of the respondent (**Error! Reference source not found.**). If respondents are the AI/BD users, they will identify the process industry in which they operate. If the respondents are service providers, they may select more than one sector, based on the ones they serve (i.e. the sector in which the company's customers operate). Respondents will be chosen with the following profiles: CEO, CTO, CDO, IT managers, production managers. Company size and respondent's experience is useful when analysing the results and calculating the CUBE dimensions.

Table 8. List of cover questions

1.1	**Country:**	
1.2	**Please specify if, concerning AI/BD your company:**	Uses/apply AI/BD technology
		Provides AI/BD technology on the market
1.3	**If you are an AI/BD technology provider, in which sector(s) your customers operate?**	Cement
		Chemicals
		Ceramics
		Engineering
		Minerals
		Non-ferrous metals
		Water
		Steel
		Other, please specify: ______________________
1.4	**If you are a user of AI/BD technologies, which is your industrial sector?**	Cement
		Chemicals
		Ceramics
		Engineering
		Minerals
		Non-ferrous metals
		Water
		Steel
		Other, please specify: ______________________
1.5	**Company Size:**	
		Under 10 employees
		10 to 49 employees
		50 to 250 employees
		251 to 500 employees
		More than 500 employees

1.6	**Position:**	
		CEO/CFO/CTO/CIO
		Production Manager
		Supply Chain Manager / Logistics Manager
		Purchasing Manager
		Operations Manager
		General Manager
		Researcher
		Senior Researcher
		Other, please specify: ______________________________
1.7	**Years of experience:**	
		< 5
		5-10
		11-15
		16 - 20
		> 20

9. Annex 2 - User profile of the questionnaire

Phase 2: questions at company level

Phase 2 questions focus on the company level and, in particular, the domains related to organisation, strategy, and people. Based on the company type of the respondent (question 1.2), one of the lists of questions, either for the users (**Error! Reference source not found.**) or providers (**Error! Reference source not found.**) is asked.

Please consider your company's approach to AI and BD technologies. To what extent do you agree/disagree with the following statements? (i.e. Level 1: Completely disagree; Level 4 Completely Agree)"		**level 1**	**level 2**	**level 3**	**level 4**
1	**Company approach to AI/BD related to Strategic issues**				
1.1	Decisions on AI/BD is part of company's strategy as an important contribution to our business goals.				
1.2	Within company's culture there is a strong interest in AI/BD, i.e. we run AI/BD initiatives, we implement a data-driven approach guiding our decision making, and AI/BD is taken into consideration in our change management activities.				
1.3	AI/BD applications are considered as value adding activities to reach competitive advantage.				
1.4	The monitor and control of the ELSI of the AI/BD are part of the company's strategy.				
1.5	Strategies to face ELSI (Ethical, Legal, Social Issues) are transparently defined and communicated. All the ELSI are adapted to the regulations and verified for compatibility of corporate strategies				
2	**Company approach to AI/BD related to organisational issues**				
2.1	AI/BD applications are transparently governed i.e. specific tasks are formalized in governance roles (CDO/CTO) at corporate level.				
2.2	AI/BD responsibilities are well tied to the organisational structure, centralised and supported by top management.				
2.3	Part of the budget is specifically allocated to AI/BD projects.				
2.4	The privacy in AI/BD applications is handled through the governance and monitoring of data access, data protection, and regulation alignments.				
2.5	In my company, the division of responsibilities of AI/BD management between corporate level and functions is transparent and well defined.				

3	Company approach to AI/BD related to workforce issues				
3.1	Employees are engaged in the AI/BD initiatives, they have the skill level and abilities needed to develop and manage AI/BD projects.				
3.2	The AI/BD skill development is associated to specific formal training programmes and is also reflected in job descriptions.				
3.3	The staff in my company is fully engaged and is aligned with the fast-paced technological evolution brought by AI/BD.				

Phase 3: Technology-process identification

The respondents in this phase are asked to identify the technologies they use in each of the processes included in the CUBE. They will be assisted by a glossary for each technology and process based on the one developed in D1.3 and reported in annex 4 for more accurate responses. In particular, compared to the list of technologies identified in D1.3 it was decided to propose a simplified version for the AI in order to reduce survey complexity for the respondents.

Table 9. Question for identifying the technologies for each process

(AI/BD user) Which technologies does your company apply for each process?		**Process**					
		Market trends and open innovation	Product customisation	Predictive maintenance	Supply chain management	Process control and optimization	Research and innovation
	Technology						
AI1	Natural language processing						
AI2	Object and spatial recognition						
AI3	Machine learning						
AI4	Expert systems						
AI5	Case based reasoning						
AI6	Intelligent agents						
BD1	Data visualization						
BD2	Data processing						
BD3	Data protection						
BD4	Data management						
BD5	Computing and storage Infrastructures						

Phase 4: Technological questions

For each technology marked as “applied” in phase 3, the respondents are asked to specify the maturity level of the technological aspects listed in **Error! Reference source not found.**. The questions are designed so that they encompass different aspects of the AI/BD applications and reflect the development of the AI-CUBE MLA framework (as described in Section 5 of this deliverable). They include the integration of technologies in the processes, the role of employees in interfering when necessary and monitoring the application of technologies, risk management, and AI/BD role in decision making. With regard to the data aspects, the questions are aimed at assessing the data availability, richness, transparency, frequency, and analysis capabilities.

Table 10. Technological questions (Process-technology specific)

User of AI/BD: Considering each technology that you use for your processes, please answer to what extent you agree or disagree with the following statements. (Level 1: completely disagree; Level 4 Completely agree)		**level 1**	**level 2**	**level 3**	**level 4**
4.1	In the specific process under consideration, AI/BD is used throughout different steps and is integrated with other applications.				
4.2	There is an automated level of design and evaluation for human-in-the-loop in my company's AI/BD functions.				
4.3	The algorithms and tools applied in this process are flexible enough to balance the AI/BD and human intervention in dealing with risks.				
4.4	All major decisions taken in the process are evidence-based and grounded in data generated by AI/BD, and users are trained to interpret data on a regular base.				

User of AI/BD: For each technology that you use for your processes, please answer to these questions related to data (Level 1: completely disagree; Level 4 Completely agree)		**level 1**	**level 2**	**level 3**	**level 4**
5.1	A large selection of internal and external data is available to satisfy all information needs with best possible data for the process under consideration.				
5.2	Data related to the process are handled in a transparent way towards the rest of the company.				
5.3	Internal and external data handled by AI/BD are updated in real-time to manage the process.				
5.4	Quality of data handled by AI/BD in the process is very good in terms of frequency of collection, completeness of data, formatting, unique identification of source				
5.5	The AI/BD has the capability to process all forms of unstructured data (e.g., text analysis) necessary for the decision to be taken.				

10. Annex 3 - Provider profile

Table 11. Questions for the providers of AI/BD

Please consider your perception for the company approach to AI and BD technologies showed by your clients operating in the process industry. To what extent do you agree/disagree with the following statements? (i.e. Level 1: Completely disagree; Level 4 Completely Agree)”		level 1	level 2	level 3	level 4
1	**Strategic issues in AI/BD**				
1.1	In process industry, decisions on AI/BD is part of company's strategy as an important contribution to business goals.				
1.2	In process industry, there is a strong interest in AI/BD, i.e. there are AI/BD initiatives, companies implement data-driven approaches, and AI/BD is taken into consideration in change management policies.				
1.3	AI/BD applications in process industry are considered as value- adding activities to reach competitive advantage.				
1.4	In process industry, strategies to face ELSI (Ethical, Legal, Social Issues) are transparently defined and communicated. All the ELSI are adapted to the regulations and verified for its compatibility of corporate strategies				
1.5	The control of the ELSI of the AI/BD are part of the company strategy in process industry.				
2	**Organisational issues in AI/BD**				
2.1	Companies transparently govern AI/BD i.e. specific tasks are incorporated in governance roles (CDO/CTO) at corporate level.				
2.2	AI/BD responsibilities are well tied to the organisational structure, centralised and supported by top management.				
2.3	Companies allocate part of the budget specifically for AI/BD projects.				
2.4	The privacy in AI/BD applications is handled through the governance and monitoring of data access, data protection, and regulation alignments.				
2.5	The division of responsibilities of AI/BD management between corporate level and functions is transparent and well defined.				
3	**Workforce issues in AI/BD**				
3.1	Usually employees are engaged in the AI/BD initiatives, they have the skill level and ability needed to develop and manage AI/BD projects.				

3.2	Companies associate AI/BD skills development to specific formal training programmes				
3.3	The staff is fully engaged and is aligned with the fast-paced technological evolution brought by AI/BD.				

Phase 3: Technology-process identification

The respondents in this phase are asked to identify the technologies they provide for each of the CUBE processes. They will be assisted by the glossary for each technology and process for more accurate responses.

Table 12. Question for identifying the technologies for each process

4. (AI/BD provider) Which technologies are mostly used in process industry?		Process					
		Market trends and open innovation	Product customisation	Predictive maintenance	Supply chain management	Process control and optimization	Research and innovation
	Technology						
AI1	Natural language processing						
AI2	Object and spatial recognition						
AI3	Machine learning						
AI4	Expert systems						
AI5	Case based reasoning						
AI6	Intelligent agents						
BD1	Data visualization						
BD2	Data processing						
BD3	Data protection						
BD4	Data management						
BD5	Computing and storage Infrastructures						

Phase 4: Technological questions

For each technology claimed as provided in phase 3, the respondents are asked to respond to the following questions which are designed so that they encompass different aspects of the AI/BD applications. They include the integration of technologies in the processes, the role of employees in interfering when necessary and monitoring the application of technologies, risk management, and AI/BD role in decision making. With regard to the data aspects, the questions are aimed at assessing the data availability, richness, transparency, frequency, and analysis capabilities.

Table 13. Technological questions (Process-technology specific)

For the chosen technology and application to related process, please select to what extent you agree/disagree with the following statements (i.e. Level 1: Completely disagree; Level 4 Completely Agree):		**level 1**	**level 2**	**level 3**	**level 4**
4.1	For the specific process under consideration, AI/BD are used by the companies throughout different steps and are integrated with other applications.				
4.2	There is an automated level of design and evaluation for human-in-the-loop when applying AI/BD.				
4.3	The algorithms and tools applied by the companies in this process are flexible enough to balance the AI/BD and human intervention in dealing with risks.				
4.4	All major decisions taken in the process are evidence-based and grounded in data generated by AI/BD, and users are trained to interpret data on a regular base.				

For the chosen technology and application to related process, please select to what extent you agree/disagree with the following statements (i.e. Level 1: Completely disagree; Level 4 Completely Agree):		**level 1**	**level 2**	**level 3**	**level 4**
5.1	Usually companies can rely on richness of data with large selection of internal and external data available to satisfy all information needs with best possible data for the process under consideration.				
5.2	In process industry, data related to the process are handled in a transparent way towards the rest of the company.				
5.3	Usually companies can rely on internal and external data handled by AI/BD and updated in real-time to manage the process.				
5.4	Quality of data handle by AI/BD is very good in terms of frequency of collection, completeness of data, formatting, unique identification of source.				
5.5	The AI/BD has the capability to process all forms of unstructured data (e.g., text analysis) necessary for the decision to be taken.				

11. Annex 4 - Glossary of the Technology Categories (D1.3)

Artificial Intelligence

Natural language processing - (NLP) subfield of linguistics, computer science, and artificial intelligence concerned with the interactions between computers and human language, in particular how to program computers to process and analyse large amounts of natural language data. Data can be in the form of written text (typically unstructured or semi structured, such as a quality control report or management report or a comments/chat section of a web application) or human speech recognition (recorded or in real time). *Applications include machine control, interactive robots, and automatic synthesis and information retrieval of industrial information captured in a textual form (e.g. reporting).*

Object and spatial recognition – technology related to computer vision and image processing that deals with detecting and recognising instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos. Spatial recognition deals with locating the objects in some spatial reference, such as an “x, y, z” coordinate or "bounding box". Applications include industrial robots and autonomous vehicles (which are increasingly used in warehouse and storage installations); recognition of objects and components during "picking”; SLAM (Simultaneous localization And Mapping).

Machine learning – Study of computer algorithms that typically train/build data models which can learn from a historical dataset and thus are said to “learn from experience” represented in the data. ML is considered a sub-area of Artificial Intelligence. *Applications include as computer vision, process simulation and predictive maintenance.* Three main categories of ML are **“supervised learning”** (known historical results/labels exist), **“unsupervised learning”** (no labels are available for training) which can use pattern matching to discover underlying structures and **“reinforcement learning”** where a “teacher” is in the loop (may be human or another algorithm) to give “reward” feedback for correct decisions. Another important and more recent type of ML is **“deep learning”** which uses artificial neural network algorithms with many layers (hence “deep”). *Applications include: computer/machine vision, speech recognition, natural language processing, audio recognition, machine translation, bioinformatics, image analysis, material inspection, among others.*

Expert systems – Computer systems which emulate the decision-making or diagnostic ability of **human experts**. Designed to solve complex problems by reasoning through bodies of knowledge, represented mainly as **“if–then-else”** rules instead of conventional computer code. *Applications include complex process control, intelligent planning, setting calibration parameters, predictive maintenance and diagnosis, among others.*

Case-based reasoning – (CBR) process of solving new problems based on the solutions of similar past problems; is an example of analogy solution making which humans commonly use every-day to solve problems. CBR has four key steps which are implemented as a computer application: **“Retrieve”** (obtain previous cases), **“Reuse”** (adapt previous case to new situation), **“Revise”** (test and further adapt as necessary), **“Retain”** if the new adapted case has resulted effective, store it for future use.

Intelligent agents – In general refer to a set of processes (typically asynchronous) which interact between themselves and with the environment in an “intelligent” manner to achieve some goal.

Multi-agent systems (i.e. hundreds or more of agents) can be used for the creation of **Cyber-physical systems** (CPS) as systems in which a mechanism is controlled or monitored by computer-based algorithms. A CPS is typically designed as a network of elements that interact with each other via physical inputs and outputs, related to the fields of robotics and sensor networks.

Big Data

Data visualization - interdisciplinary field of study whose object is the representation of data in graphical format. As a form of communication, it is particularly efficient when the amount of data to be represented is large, for example in the case of time series and/or Big Data. *Key applications include "dashboard" displays for complex process real-time control systems, and management decision support systems.*

Data processing – collection and manipulation of items of data to produce meaningful information. It may involve various processes, including: **validation** (ensuring that supplied data is correct and relevant), **sorting** (arranging items in some sequence and/or in different sets), **summarization** (reducing detailed data to its main points), **aggregation** (combining multiple pieces of data), **analysis/interpretation**, **reporting** and **classification** (separation of data into various categories).

Data protection – relationship between the collection and dissemination of data, technology, the public expectation of privacy, and the legal and political issues surrounding them. It is also known as data privacy or information privacy. In industrial terms it can be related to cyber-security and the protection of installations from cyber-attacks, as well as industrial secrets, patents and confidentiality. In the European context, the General Data Protection Regulation (EU) 2016/679 (GDPR) is a regulation in EU law on data protection and privacy in the European Union (EU) and the European Economic Area (EEA). Its primary aim is to give individuals control over their personal data and to simplify the regulatory environment for international business by unifying the regulation within the EU.

Data management - comprises all disciplines related to managing data as a valuable resource. In a digital context, it offers tools to facilitate the management of data and improve performance, consisting of an integrated, modular environment to manage enterprise application data, and optimize data-driven applications over its lifetime. It includes the following objectives: produce enterprise-ready applications faster; improve data access, speed iterative testing; automate and simplify operations; support business growth.

Computing and storage infrastructure - provides the hardware and services that other systems and services are built on. It has different components and some of the key ones are listed as follows: file and disk storage service such as file servers, file backup, long-term archive and ftp services; networks; authentication, the means by which users log in and identify themselves; authorisation by which a service determines whether an authenticated person should have access to that service; virtual hosting to provide a managed platform for hosting Windows, Linux and Unix services on a reliable virtualisation platform; cloud computing services to provide a platform to self-provision server infrastructure to support both employees and clients.

12. ANNEX 5 - GLOSSARY OF THE PROCESSES (D1.3)

Market trends and Open Innovation – Awareness of market trends leads to adapt company products/services to future demands and customers by obtaining information (strategic and tactical) and data from internal and external sources. Open innovation is closely related to market trends as it taps into knowledge and assets available within and beyond the single company, along with any other relevant data, to improve internal in line the market evolution. **Marketing data analysis and trend identification is a key aspect of data exploration and modelling.** Sub-processes: Sales, Customer Relationship Management, Consumer Behaviour Analysis, Market Scenario Analysis, Demand Management and Forecasting.

Product design/customization – Basic activity of conceptualizing, creating, and evolving products that solve a customer's/user's problems or address specific needs in a given market. Product customization is closely related to design in alignment with particular customer's desires, increasing customer perceived value to a product. **Digital design tools can potentiate creativity and finding innovative and competitive products.** Sub-processes: Product/Service Design and Customization, New Product/Service Introduction, Design.

Predictive maintenance – Series of actions and techniques applied to detect possible failures and defects of machinery in the early stages, prevent these failures causing major failures and future stoppages. The objective is to maintain a certain level of service in the given process industry, which requires the capture of a lot of data from sensors of the machines and information from periodic reports and planned maintenance. **Key potential field for big data processing and data modelling of data from the sensors and other data/information.**

Supply chain management (re)configuring and scheduling - Process of planning, executing and controlling the operations of the supply network with the purpose of meeting customer needs as effectively as possible. Complex requirements, deadlines and restrictions are often conflicting/overlapping; **hence data models and intelligent planning can help to find optimum configurations which obtain an equilibrium between different prioritized requirements and commitments.** Sub-processes: Procurement, Production, Storage, Distribution, Reverse Logistics, Network Design, Logistics Systems (replenishment/distribution) design, Supplier Relationship Management, Contract Management, Sourcing Analysis, Resource allocation/utilization and scheduling, Process Redesign.

Process control and optimization - Discipline of adjusting a process to maintain or optimize a specified set of parameters without violating process constraints. **Digital twins are a solution for modelling and simulating complex processes, thus avoiding expensive trial and error calibration, for example.** Sub-processes: Process and Equipment Monitoring, Quality control and monitoring, Process Redesign.

Research and innovation management, planning and design – Guaranteeing that the necessary resources (human, physical, and financial) are in place and are effective for a required research and innovation plan and requirements. M**any digital technologies play a role here, e.g. data management, intelligent planning, data visualization, cyber-physical systems, data understanding and characterization, natural language processing, etc.** Sub-processes: Scenario Based Analysis< Optimization/Simulation, HR Management, Risk Management, Collaborative/Joint Innovation Platform Development, Process Redesign. *Note that "research" is considered as "applied research". Also, "planning research" is differentiated from "logistics planning" and "design research" is differentiated from "product design".*