



## D2.4 REPORT OF THE ASSESSMENT OF IMPACT

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## List of abbreviations and definitions

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

Abbreviation	Definition
AI	Artificial Intelligence
BD	Big Data
SPIRE	Sustainable Process Industry through Resource and Energy Efficiency
R&D	Research and Development
BDA	Big Data Analytics
KPI	Key Performance Indicator

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## 1. EXECUTIVE SUMMARY

This deliverable aims to describe the work conducted in T2.3 within WP2. We mainly report the development of a framework for assessing impact of AI&BD in process industry and present the result of a pilot test of this approach with a workshop.

We first provide a brief discussion of why it is crucial to perform a proper assessment of the impact (economic, social, environmental) AI & BD will have in process industry. The number of examples showcasing the benefits of deploying AI & BD solutions have been increasing recently. However, because of the significant investment required to deploy such technologies/solutions (e.g., \$39 million for the three-year total cost of ownership for an IBM PureData System for Analytics, see Müller et al., 2018), companies will not be willing to commit to such large investments unless they can be justified in the anticipation of potential positive impact AI & BD will have. The problem is that the financial, operational, social, and environmental impact is quite difficult to measure and quantify in general. The situation is especially complicated in the process industry, where the adaption rate of such technologies is somewhat slower compared to some other industries, and therefore decision makers usually go for such investment based on “perceived” benefits, as shown in the results of WP1 of AI-CUBE.

After discussing the costs of AI & BD deployment and the potential impact that has been realized so far in similar settings, we move on with the review of the preliminary impact indicators identified in the A.SPIRE positioning paper titled “ARTIFICIAL INTELLIGENCE in EU PROCESS INDUSTRY A VIEW FROM THE SPIRE cPPP”. We have carefully revised this list of indicators and complemented it by reviewing the relevant literature on impact assessment. We then present the impact matrix, considering the processes in the industry, and group them under 4 different dimensions (Human, R&D, Plant and Value Chain).

The AI-CUBE Impact Matrix compiles the main impacts identified, the characteristics or “why” AI & BD will have a particular impact, and the associated Key Performance Indicators (KPIs) to provide the decision maker an objective tool to measure the impact. This matrix has been validated by consulting with a few experts with experience in projects related to the use of AI&BD in the process industry. In order to simplify this matrix so that the decision makers evaluating the impact are not overwhelmed by the amount of information they need to provide and process, we further reduced the size of the matrix. For this purpose, the AI-CUBE online survey provided the most relevant impacts for the industry, which yielded the subset of impact indicators. 5 impact indicators (as opposed to the 20 impact indicators in the original matrix) in the end were selected as the most important, according to this survey. The most voted impacts were: (1) More efficient processes - improve industrial production, (2) More effective maintenance, (3) Strengthen workforce, (4) Increased profitability, and (5) Better quality products.

Later, we continue with the assessment of these impact indicators by the relevant stakeholders. Our purpose here is to understand how different actors perceive the benefits of AI & BD deployment in the process industry. We aim to understand whether these stakeholders agree on the impact or they have opposing views as to how the industry will be affected, which would eventually either foster joint efforts in deploying such solutions or impede. The Multi-Actor Multi-Criteria analysis (MAMCA) methodology was employed. The scenarios (Full Integration, Business as Usual, Divergence, and Human Free) in relation to the adaption rates and the manner AI & BD solutions are deployed in the future and the actors (Production/Plant Manager, Sales/Services Manager, Talent Manager, Top Management, and AI & BD Technology Providers/Consultants) are defined in this methodology. We also present the criteria (the 5 impact indicators mentioned in the previous

paragraph) and the associated KPIs to aid in impact evaluation. This framework along with the definition of the scenarios, actors, criteria, and the KPIs is presented as a tool to help managers make informed decisions in regards to impact evaluation under different scenarios.

Finally, we presented the results of a workshop organized, where participants assumed the roles of above actors defined in the MAMCA methodology. Each actor evaluated the impact under different scenarios. We observe that this pilot test of the methodology is quite effective in facilitating a discussion leading to a more objective evaluation of impact of AI&BD technologies in the process industry. We present easy-to-understand visualizations of the evaluation outcomes. All 5 impacts were confirmed as important or very important to all the stakeholders, in almost all scenarios. The lowest score (although still high) was for “increased profitability” as it was not very clear how to connect the associated operational benefits to the profits in the end and the fact profits are regulated by many other factors (e.g., political). There are some differences in terms of how different actors evaluate the impact (e.g., plant manager focusing more on effective process), but we did not observe stark differences that would deter companies from making investments in AI & BD solution.

The deliverable ends with a brief discussion of the likelihood of these different scenarios happening in the medium to long term, and potential impact and cost of deployment. There is a consensus among workshop attendees that the expected level of AI & BD deployment will deepen the gap between big and small companies within 5 to 10 years. Big companies are already investing in AI & BD technologies, which might lead to some small companies being displaced from the market or lose significant market share. On the other hand, Full Integration of AI & BD technologies are expected to be a reality within approximately 20 years, in the anticipation that organizations will overcome significant challenges in data centralization, integration, and verification in the industrial plants.

The results of this deliverable will be an input to the roadmap design in WP 4 for the SPIRE community specifically and the process industry at large.

## 2. 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.



### 3. OBJECTIVES OF THIS DELIVERABLE

The objective of this deliverable is to describe the work conducted in T2.3 within WP2. Our main goals in Task 2.3 are as follows:

- To develop the initial, comprehensive AI-CUBE Impact Matrix based on desk research and A.SPIRE positioning paper with impact indicators,
- To modify the above impact matrix, identifying the critical impact factors based on surveys and consultations with industry stakeholders to provide a practical and easy to use framework (with a reasonable number of impact factors and associated KPIs), that could be used in performing a rough impact assessment and make an informed decision before committing to investments in AI&BD solutions.
- Provide a framework for Impact Assessment (Using the Multi-Actor Multi Criteria (MAMCA) approach) that solicits the views of different departments and functions (aka actors) with different objectives to ensure acceptance by all parties potentially leading to successful deployment of AI & BD solutions (or to figure out if there are stark differences in the expectations in relation to the impact AI & BDA will have, potentially leading to a lack of coordination/collaboration among these actors).
- To define different future scenarios that represent different adaption rates of application of AI & BD solutions as well as how they are deployed (e.g., amplifying human potential or replacing human workforce), and understand if these scenarios in the future changes the perceptions of the relevant stakeholders and their willingness to invest in such solutions,
- Get a clear overview of the expectations of the experts in process industry in relation to the impact of AI & BD on more efficient processes, more effective maintenance, strengthened workforce, increased profitability, and better-quality products.

The output of this deliverable, specifically the AI-CUBE Impact Matrix and the impact evaluation methodology (MAMCA), will be an input for the main goals of AI-CUBE:

- 1) providing insights regarding the status of AI & BD deployment in the process industries,
- 2) forming part of the Business Model Innovation Game to be developed, helping decision makers assess the impact in different business cases for different SPIRE sectors, and
- 3) forming bases of the development of the AI-CUBE pathways towards further development of AI & BD to better deploy in the light of implementation cases and future business cases (e.g. using the AI-CUBE Impact Matrix to assess potential impact of new AI & BD driven business cases for the process industries).

## 4. IMPACT OF ARTIFICIAL INTELLIGENCE AND BIG DATA IN PROCESS INDUSTRY

Based on the recent case studies reporting positive expectations in regards to the potential of AI & BD solutions, an increasing number of firms contemplate investing more in such technologies (for examples, see Müller et al. (2018), Chen et al. (2015), **Amplifying Human Potential: Towards Purposeful Artificial Intelligence** by InfoSys (2017)). This creates a competitive pressure from stakeholders (both from within and outside the supply chain) as the deployment of artificial intelligence and big data analytics might become “qualifiers” instead of “winners” in the near future. Companies lagging behind might lose competitive advantage and even risk being disintermediated.

However, the lack of a standard definition of what an AI & BD solution/technology is, what “big data” really is, and a large number of processes and the associated KPIs that might be affected makes the impact assessment of such solutions fairly difficult. Moreover, AI & BD is more of a transformational/innovative solution that requires significant investment, with potential impacts to be observed in only some processes in the medium to long term because of lags due to learning and adjustments.

This section provides a summary of the investment that needs to be done for a successful deployment of AI & BD as well as the potential impact on a select number of processes. We present our findings based on desk research investigating the impact of similar technologies/solutions, the A.SPIRE paper on ARTIFICIAL INTELLIGENCE in EU PROCESS INDUSTRY A VIEW FROM THE SPIRE cPPP, and consultation with project consortium partners as well as industry experts.

The first step in understanding whether widespread deployment of AI & BD solutions in the process industry will take place or not is a careful analysis of the Return on Investment (ROI). In order to enable AI & BD deployment, companies not only need to make significant investments in purchasing and running AI & BD solutions (e.g., hardware, software, maintenance, energy), but also implement organizational changes and develop training programs (Manecke and Schoensleben, 2004). Kamble and Gunasekaran (2020) also investigate the types of assets for desired Big Data Analytics (BDA) Capabilities. They mention *human assets* (e.g., capacity to understand data, expertise in handling IT systems, data visualization skills, dedicated business intelligence teams), *technology assets* (e.g., compiling metadata, creating ontologies/typologies, ability to access third-party data, ensuring compatibility among multiple IT platforms), and *relationships assets* (e.g., external help to adapt and integrate, strategic partners/suppliers of specialist services). Müller et al., 2018) provide some examples as to how costly these investments might get. For example, “*the three-year total cost of ownership for an IBM PureData System for Analytics, an appliance for big data processing, is estimated to be \$39 million. The overall costs for a comparable Cloudera Hadoop cluster for the same period sum up to more than \$50 million*”. The ability to estimate the potential impact of such investments as well as changes in performance due to organizational/technological changes in processes is key to assess the net impact of AI & BD solutions. Top management would only be able to undertake such costly initiatives if the return from these investments outweigh the costs.

In what follows, we therefore focus on the potential impact AI & BD would have. AI & BD solutions have promising economic consequences. The ultimate goal is generally to achieve higher profits as a result of increased sales, higher profit margins due to cost reductions as well as greater pricing precision. Toorajipour et al. (2021) state that AI leads to problem solving with higher accuracy and speed with larger amounts of input data. To name a few specific improvements, artificial intelligence is supposed to lead to more effective direct marketing, improved product life-cycle

management, more accurate forecasts, better quality control through data mining, better supplier selection, intelligent maintenance, resource balancing, improved supply chain visibility and enhanced risk management.

According to the research by **Chen et al. (2015)** use of BDA helps “information replace inventory”. Specifically, it leads to less asset-intensive buffers in inventory or capacity because of reduced uncertainties in demand and supply availability as well capacities. In addition, the authors mention some intangible benefits such as establishing knowledge creation routines, learning between departments/firms resulting in better resource configuration/utilization in core business functions (e.g., optimization of inventory replenishment policies, distribution plans). Moreover, BDA has the potential to make managers more alert to opportunities for business growth (e.g., new product offerings, better pricing, personalized products/services), and the impact seems to be more pronounced in highly dynamic business environments.

**Lee et al. (2018)** analyse the benefits AI would bring, and summarize the value drivers of AI in terms of *process efficiency*, *process enhancement*, and *product or service innovation*. The authors provide specific examples that clearly show the positive impact of AI, some of which are: better product design through reinforcement learning leading to a sturdy yet light (45% reduction in weight) airline partitions as a result of collaboration between Airbus and AutoDesk; increased profitability using machine learning analysing the data from 50,000 sensors for better estimates of prices of scrap and finished steel, projected demand, wear and tear on their factory as a result of collaboration between Big River Steel (BRS) and Noodle.ai; significant increase in efficiency (i.e., higher user participation) in energy campaigns through machine learning and optimizing customer segmentation for campaigns based on household-level energy usage data, aggregated demographics data and weather forecasts at OhmConnect.

As far as the process industry is considered, the following table provides a summary of the results of implementing AI technology on different SPIRE sectors per process and issue addressed, based on the literature review performed in WP1 (D1.3 Review and Update of the Identified Macro Applications Areas Plan):

**Table 1. Results of some AI and BD implementation cases in different SPIRE sectors (based on literature review performed in WP1).**

Sector	Process addressed by AI & BD	Concerned issues	Results achieved
<b>Water</b>	(Model predictive) process control and optimization Predictive maintenance Research and innovation management, planning and design	Waste water processing, clean water processing. Complex processing chain, large processing volumes, yield.	Cost reduction, improved efficiency, energy saving, increased sustainability, optimized performance, data management
<b>Steel</b>	(Model predictive) process control and optimization Supply Chain Management	Furnace, smelting. High energy consumption, risk to humans, quality control, logistics, Value Chain.	Improved performance, product optimized, successful process redesign, product quality prediction, informed decisions and workforce time saving, productivity/yield increased, process optimized (energy and time savings, i.e.)
<b>Minerals</b>	(Model predictive) process control and optimization Predictive maintenance	Milling of raw material, mining/extraction. High energy consumption, security and human safety, scheduling/planning, security, automation, remote monitoring.	Trends and market prediction, process optimized, improved quality control, better fault detection and diagnosis, informed decisions taken, data processing implemented, process improvement, process control improved, workforce safety improved, data protection achieved

<b>Non-ferrous metals</b>	(Model predictive) process control and optimization Predictive maintenance	Furnace, smelting. High energy consumption, risk to humans, scrap quality control, logistics.	Improved product characterization, informed decision making, optimized production process, process and consumption understanding, improved fault forecasting
<b>Engineering</b>	(Model predictive) process control and optimization Predictive maintenance Supply Chain Management	Fault detection, quality assurance. Predictive maintenance, data quality, sensor data capture.	More efficient production, higher quality, improved customers needs identification, increased knowledge
<b>Chemicals</b>	Supply chain management (re)configuring and scheduling (Model predictive) process control and optimization Research and innovation management, planning and design Supply Chain Management	Conversion of materials. Waste avoidance, process complexity, reliability, production planning, continuous sensor-based monitoring process control logistics, goods shipments tracking.	Energy saving, improved process understanding and optimization, increased sustainability, improved quality control, data management achieved
<b>Ceramics</b>	Product customization/design Supply chain management (re)configuring and scheduling (Model predictive) process control and optimization Research and innovation management, planning and design	Raw material processing, firing, finishing. High energy consumption, reduce defects (cracking/foaming)	Improved defects detection and quality control, product characterization, process optimization, optimized products, better production management
<b>Cement</b>	Predictive maintenance (Model predictive) process control and optimization Product design Research and innovation management, planning and design Supply chain management	Kiln, firing, material processing. High energy consumption, predictive maintenance, predict process behavior, supply chain, remote operation.	Product characterization, process improvement, higher efficiency, increased sustainability, better process control

According to the research by Müller et al. (2018), there is a 4.1% (on average) improvement in firm productivity because of live BDA assets. The average improvement is even larger for IT-intensive (6.7%) or highly competitive (5.7%) industries. A similar study by Brynjolfsson et al. (2011) investigating the impact of decision making based on data and business analytics suggest that “firms that adapt data-driven decision making have output and productivity that is 5-6% higher than what would be expected given their other investments and information technology usage”. According to the report “Amplifying Human Potential: Towards Purposeful Artificial Intelligence” by InfoSys (2017), the result of a poll with 1600 global business decision makers that already implemented AI technology indicates an expectation of a 39% increase in revenue by 2020, as well as a 37% decrease in costs.

However, firms are not just interested in economic consequences. Recently, sustainability (e.g., lower energy use, improved waste collection/management, new opportunities for recycling/remanufacturing and better estimation of quantity, location, and quality of used materials), social welfare (e.g., impact on unemployment, labor supply and demand, labor safety), agility and resilience (e.g., faster detection of anomalies and faster action in response to disruptive events) are also on the radar of top management in many sectors.

Accurate estimate of the potential impact on economic, social, sustainability, and resilience related objectives is only possible if the decision makers know what “processes” to focus on. Therefore, in the last part of this section, we report our findings as to which processes are relevant for impact

assessment of AI & BD in general, and in process industry in particular based on the processes previously defined in WP 1 of the AI-Cube Project.

Supply chain management processes (based on the well-known SCOR model considering “plan, source, make, deliver, and return” stages) such as product design, sourcing, purchasing, production, distribution, network design, inventory optimization, after-sales customer services are also potential candidates for AI & BD deployment. **Chen et al. (2015)** mention that BD solutions improve core business processes such as marketing, product/service development, human resources, operations. **Toorajipour et al. (2021)** list marketing (e.g., pricing, segmentation), logistics (e.g., inbound logistics operations, lot-sizing), production (e.g., production planning/monitoring, quality), supply chain (e.g., facility location, supplier selection), and maintenance systems as processes that are to be impacted by artificial intelligence in the realm of supply chain management. In addition, they mention crisis management and sustainability as subfields that will also benefit from AI & BDA deployment.

The number of processes to be considered is large, and each process is connected to a number of key performance indicators. Measuring the impact of any solution on all of these processes and all the associated KPIs is therefore a Herculean task, which requires significant time and effort. By the same token, **Dumitrascu et al. (2020)** also choose top 5 KPIs for the 9 subsystems they identify to measure the impact of AI on supply chain performance and sustainability in the Automotive Industry. These subsystems are the management of: demand management, supplier management, contract management, product development, procurement/purchasing, sales management, warehouse management, production management, and distribution management. Some examples to KPIs in the same study are order fulfilment costs, supplier lead time, contract breaches due to non-compliance, time to market new products, material acquisition cost, % sales growth, warehouse space utilization, production lead time, delivery cost per order.

In the next section, we provide details on the methodology used to assess the potential impact. In particular, we explain which impact factors (based on the dimensions specified in the A.SPIRE document) and KPIs are chosen through the survey and workshops, as well as how the perception of different stakeholders are obtained and analysed via the Multi-Actor Multi-Criteria Analysis (MAMCA).



## 5. METHODOLOGY AND MODEL

In this section, we discuss the methodology used in the impact assessment. The major steps are:

- Identifying the relevant processes and the associated KPIs,
- Further reducing the number of impact factors and related KPIs based on the results of the online survey for process industry,
- Grouping those under the dimensions as specified in the A.SPIRE document,
- Applying the MAMCA approach (defining scenarios, identifying actors).

First of all, in order to reduce the number of processes and KPIs to work with to reasonable levels, the selection of a subset of these processes and KPIs is a crucial step in our approach, similar to the work by Dumitrascu et al. (2020). In doing so, we filter through relevant processes based on desk research and keep the ones that are better candidates for AI & BD deployment with the following characteristics for further analysis:

- Processes that are highly complex and information-intensive would probably be affected more. Chen et al. (2015) identify three dimensions of supply chain processes that fit this category: (1) *coordination/integration processes* (e.g., process equipment monitoring, warehouse operations improvements), (2) *learning processes* (e.g., sourcing analysis, purchasing spend analytics), and (3) *reconfiguration process* (e.g., network design, inventory replenishment optimization).
- Most businesses have the following four main operative goals: *cost, time, quality, and flexibility, innovativeness* (Manecke and Schosbelesn (2004) and Kamble and Gunasekaran (2020)). Processes that have the biggest impact on these goals are usually the better candidates for the initial deployment of AI & BD solutions, to ensure positive return in the medium term.
- Processes where critical decisions have to be made fast would benefit more as the pressure to keep up with the pace in high-velocity markets/environments in competitive industries and the problems to bounded rationality of humans are less of a problem with the AI & BDA solutions
- According to Manecke and Schoensleben (2004), frequency with which certain tasks are repeated (e.g., decisions, sample taking, monitoring), the frequency and level of communication (between what partners communication between people/machines/tools) required, and the nature of the task that determines if the task can be processed by machines or only humans are process level characteristics that define whether a process is a good candidate for internet-based support systems.

Once we have the short-list of processes, we have identified a limited number of related KPIs to be included in the impact evaluation. We present the resulting AI-CUBE impact matrix after further reduction in the number of impact factors and KPIs based on the results of the online survey.

### 5.1 AI-CUBE IMPACT MATRIX

Based on the desk research on processes, KPIs, and the potential impact and internal brainstorming sessions among consortium partners led to a complete list of impact factors and

KPIs. These are grouped according to the dimensions defined by A.SPIRE document (i.e., people, production, plant, organization, financial, sales, services, capacitation, research and development and other services) to create the AI-CUBE Impact Matrix.

For the purpose of keeping our work aligned to A.SPIRE document, we tried to keep the impact dimensions that were identified in the referenced document (a. Impact on human/operators, b. Impact on Process/Product R&D&I, c. Impact on Plant and Plant Operations, d. Impact on Value Chains and e. Impact on organisation in factories and in companies).

Table 2 below is the final version of all the identified impacts under four final dimensions (HUMAN, RESEARCH & DEVELOPMENT, VALUE CHAIN and PLANT) and the specific KPI (in the column *Why?/KPIs*).

Table 2. AI-CUBE IMPACT MATRIX

ID	Impact on workforce (HUMAN DIMENSION)	Why? /KPIs
H1	<b>Building a more effective/efficient/creative workforce</b>	Increased number of high quality/interpretable/accessible reports with relevant/useful information generated by AI&BD tools
		A larger "number of processes" across different departments/SC entities utilizing AI&BD generated information
		Increased percent of time decisions informed by AI&BD generated information (automated or human/automated mix)
		Increased number of "best practices" aided by AI&BD technologies
		Accelerated human/operators learning (i.e., reduced time to proficiency) via more efficient and formalized transfer of operators' knowledge and best practices
		Accelerated human/operators learning via enhanced capacity to understand data (e.g., dashboards for data visualization)
		Providing scope to gain new/better insights via simplifying human-machine interface with complex processes
		Improved process for the evaluation of workforce performance (e.g., ability to better monitor KPIs, deviation from targets/objectives, employee/manager feedback, improved employee satisfaction due to fairer evaluation)
		Increased use of AI&BD supported tools for innovation training, and R&D
H2	<b>Creating more time for core business activities (problem solving, process improvement, etc.)</b>	Higher number of automated tasks that are repetitive, transactional and judgment-related
H3	<b>Improving workplace safety: Lower number of accidents and incidents</b>	AI & BD technologies used in physical tasks in dangerous working environments formerly requiring human involvement
H4	<b>Building trust across business units within an organization and within the VC</b>	Improved and fairer decisions as a result of objective data-driven AI&BD based solutions help build trust across different business units and/or SC partners

ID	Impact on R&I (R&I DIMENSION)	Why? / KPIs
RI1	<b>Enhanced capabilities to</b>	Identify critical factors/variables to be tested in experiments using AI&BD tools

	<b>design experiments and interpret results</b>	Predictive analytics based on internal/external data to understand input/output relationships in processes Quick/Reliable interpretation and statistical analysis of the results (large amount of data) of experiments/simulations using AI&BD tools
<b>RI2</b>	<b>Faster introduction of new products of superior quality (more features, increased reliability, longer lifetime, etc.)</b>	Faster and better innovation cycles using data-driven R&D systems, data-driven R&D through in-silico experimentation and advanced lab automation Better analysis of the performance of existing products for the improvement of future products based on lifecycle data Data analytics in material design and simulation in order to accelerate new product development
<b>RI3</b>	<b>Building a more flexible and customer-driven production system</b>	Increased flexibility (ability to switch production of different goods, adjust production capacity, location (production site) flexibility, input material flexibility) because of reduced efforts to change settings with the use of AI&BD tools Better customization in response to changing customer needs as a result of improved identification of customer needs, enhanced processes to differentiate products quicker and with less resources Improved marketing and design cycle, even to the extent of letting customers customizing products/services

ID	Impact on plant (PLANT DIMENSION)	Why? /KPIs
<b>P1</b>	<b>Building a more efficient production process</b>	Less rework and higher yield as a result of increase in first-time-right production Reduction in the manufacturing cycle time due to increased production rate (leading to increased yield) Improved Overall Operating Efficiency (OOE), with better performance, quality, and availability of operating time Improved Overall Equipment Effectiveness (OEE), with better performance, quality, and availability of scheduled time Improved Scheduling, Monitoring, Maintenance, and Process Management and therefore better adherence to schedule (less "behind plan" and improved schedule compliance) Supervised autonomous plants, self-organization of industrial production, and use of real-time digital-twin simulation for frequent optimization of operations
<b>P2</b>	<b>Better quality products</b>	Improved quality through reduction of number of defective units
<b>P3</b>	<b>Reducing energy consumption</b>	Process optimization identifying and eliminating inefficiencies causing unnecessary use of energy Intelligent coupling of production plants/sites with renewable energy grids, and reduced carbon footprint
<b>P4</b>	<b>Effective sourcing of energy and raw materials</b>	Better prediction of requirements and improved hybrid (spot market and contract) procurement
<b>P5</b>	<b>More automation and increased safety/quality</b>	Tedious, routine-based manual tasks replaced by devices enabled by AI&BD technologies
<b>P6</b>	<b>Reduced number of equipment failures, increased productivity and overall plant lifetime</b>	AI augmented supervision of maintenance routines and component spare parts replacement reducing equipment/plant downtime Predictive and Planned Maintenance increasing the "Mean Time Between Failures"
<b>P7</b>	<b>More responsive production systems</b>	Dedicated digitally supported teams of operators, pooled for larger plant clusters, to handle problems and unexpected events



<b>P8</b>	<b>Better integrated production systems</b>	Data (process, product, and maintenance) consolidation
		Coordinated and cooperative actions among subsystems considering potentially conflicting operational objectives
		Production data fully available for R&D and customer service activities

ID	Impact on VC (VALUE CHAIN DIMENSION)	Why? / KPIs
<b>VC1</b>	<b>Increase in the number of new/personalized products and services introduced</b>	Improved and faster innovation cycles
		More flexible production processes capable of customizing products based on customer requirements
		More efficient production processes with lower costs allowing for a larger number of changes in production parameters for customization
<b>VC2</b>	<b>Bigger market share</b>	Improved market sensing via deeper understanding of customers' experience and behaviour and better identifying new applications/markets for existing and new products
		Maintaining loyalty of existing customers via differentiated service for different customer segments, better real-time analysis of customer feedback
		Conduct highly targeted marketing campaigns, proactive sales with AI-based customer-specific forecasting and demand sensing, which could make it possible to ship goods even before the customer places orders
<b>VC3</b>	<b>Better match between demand and supply (i.e., higher customer service levels with less storage requirements)</b>	Higher demand forecast accuracy leading to adequate replenishment policies yielding optimal inventory levels
		Enhanced capabilities to monitor inventory levels (inventory record accuracy), supplier performance (disruptions, capacities, lead times, on-time-in-full delivery performance, etc.) and proactive procurement strategies
<b>VC4</b>	<b>More opportunities for horizontal/vertical collaboration and industrial symbiosis</b>	Tight coupling of production units (streams of materials and/or energy) through simulation of operating conditions of all involved plants
		Better identification of opportunities for joint sourcing practices (economies of scale in ordering), resource sharing (pooled inventories to meet customer demand, shared production capacity, shared warehouse space)
		Better understanding of waste generation/management, recycling/remanufacturing opportunities
<b>VC5</b>	<b>Increase in profitability</b>	Higher profit margins because of increased value to the customer (larger revenues collected thanks to personalized/customisable product and service offerings)
		Higher sales thanks to improved marketing campaigns, better customer segmentation, and faster new product introduction
		Cost reduction (manufacturing, delivery, design, input materials, etc.)

## 5.2 IMPACT MATRIX VALIDATION AND PRIORITIES ASSESSMENT

In order to find the most relevant impact for the process industry the list with the main impact factors from the AI-CUBE matrix included in Table 3 were added to the AI-CUBE general survey, to be filled in by the project stakeholders as well as experts in process industry and AI & BD providers using social media and mailing. The participants were asked to select a maximum of 6 impacts as the most important from their point of view. The table also includes the results of the votes obtained in the survey for each of the impacts and the most voted impacts are already in bold.

Table 3. Most important impacts of AI & BD according to the general online survey of AI-CUBE.

ID	IMPACT	PROVIDER	USER	TOTAL
H1	<b>Building a more effective/efficient/creative workforce</b>	4,6%	6,2%	<b>10,8%</b>
H2	Creating more time for core business activities (problem solving, process improvement, etc.)	0	0	0
H3	Improving workplace safety: Lower number of accidents and incidents	1,5%	1,5%	3,1%
H4	Building trust across business units within an organization and within the VC	0	0	0
R11	Enhanced capabilities to design experiments and interpret results	1,5	4,6%	6,2%
I2	Faster introduction of new products of superior quality (more features, increased reliability, longer lifetime, etc.)	3,1%	0	3,1%
R13	Building a more flexible and customer-driven production system	0	4,6%	4,6%
P1	<b>Building a more efficient production process</b>	4,6%	7,7%	<b>12,3%</b>
P2	<b>Better quality products</b>	4,6%	4,6%	<b>9,2%</b>
P3	Reducing energy consumption	0	0	0
P4	Effective sourcing of energy and raw materials	0	3,1%	3,1%
P5	More automation and increased safety/quality	3,1%	3,1%	6,2%
P6	<b>Reduced number of equipment failures, increased productivity and overall plant lifetime</b>	4,6%	6,2%	<b>10,8%</b>
P7	More responsive production systems	1,5%	4,6%	6,2%
P8	Better integrated production systems	1,5%	0	1,5%
VC1	Increase in the number of new/personalized products and services introduced	0	3,1%	3,1%
VC2	Bigger market share	0	1,5%	1,5%
VC3	Better match between demand and supply (i.e., higher customer service levels with less storage requirements)	0	4,6%	4,6%
VC4	More opportunities for horizontal/vertical collaboration and industrial symbiosis	1,5%	3,1%	4,6%
VC5	<b>Increase in profitability</b>	3,1%	6,2%	<b>9,2%</b>

The AI-CUBE online survey helped identify the most relevant impacts for the industry with a representative participation of industrial users of AI & BD technologies and AI & BD technology providers. Responses from a total of 16 participants (7 AI & BD providers and 9 technology users) were collected. The SPIRE sector participation is shown in Figure 1, in the survey the users indicated the sector their organization belong to and the providers indicated the SPIRE sectors they work with. All the sectors had at least 1 contribution, except for the Cement, the Ceramics and the Non-ferrous sectors.

The response rate was not sufficiently high to report results separately for different SPIRE sectors or different characteristics (e.g., firm size) that would be statistically meaningful (further information in the survey results and updated will be provided in WP3). However, we present the overall results, which are representative of the of the understanding of the impact of AI & BD in process industry to some extent, grouped in terms of whether respondent is a user or provider of AI&BD technology in Figure 2.

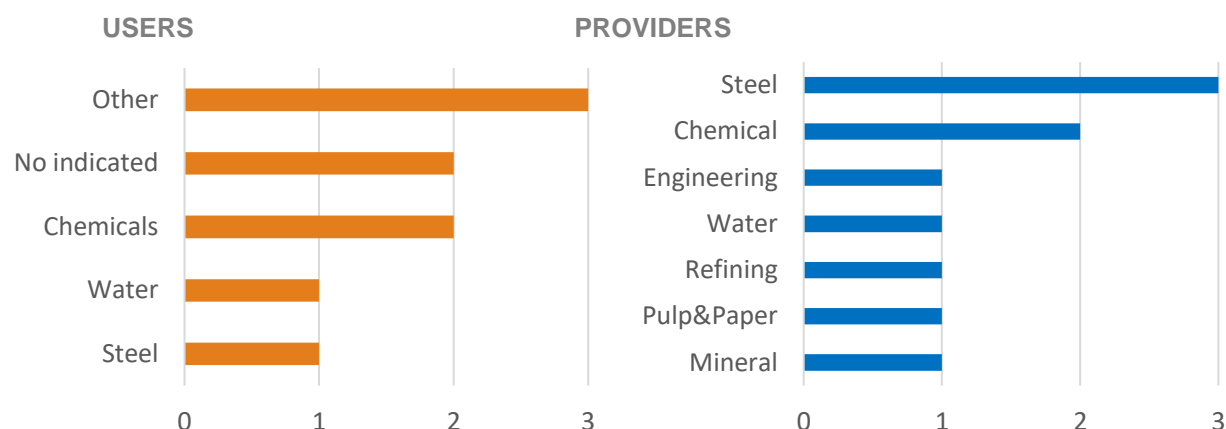


Figure 1. Sector participation in the online survey.

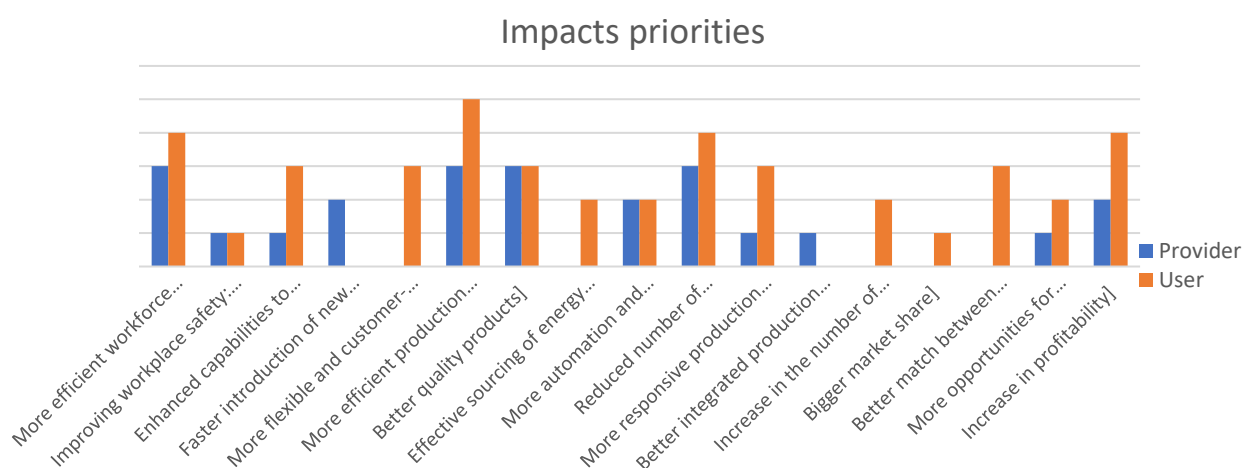


Figure 2. Prioritization of the AI-CUBE impacts from the online survey.

One, rather promising result, of the survey results is that the “users” seem to have a slightly more optimistic perception and think that AI & BD solutions will have appreciable impact compared to the “providers”. This is interesting as one would expect the technology providers to be more confident in the potential impact of AI & BD deployment.

Based on the results of the survey, 5 impact factors in Table 2 emerged as the most relevant ones for the process industry: (a) More efficient processes - improve industrial production, (b) More effective maintenance, (c) Strengthen workforce, (d) Increased profitability, and (e) Better quality products. These five impact factors will become the criteria for the MAMCA evaluation (more details in the following sections), and they will also help define the “actors” in the MAMCA approach to assess the final impact for process industry.

## 5.3 MAMCA METHODOLOGY

### 5.3.1 Introduction to MAMCA methodology

In order to obtain a widely supported and consensus-based action plan, the Multi-Actor Multi-Criteria Analysis (MAMCA) methodology (Macharis et al. 2009) is used to consult the stakeholder community.

This stepwise and scientifically sound approach allows the consortium of the project to involve a representative group of stakeholders in the process of analysis. MAMCA enables the evaluation of different alternatives by explicitly taking into account the objectives and framework conditions of the actors involved in the decision-making process.

In order to get a more detailed understanding of the MAMCA method, the seven phases shown in the Figure 3 are briefly described.

- **Step 1:** Definition of the problem and the identification of the alternatives
- **Step 2:** Stakeholder identification and in-depth understanding of each stakeholder group's objectives (these stakeholders will be key to identify the criteria, which are here equal to the objectives of the stakeholders)
- **Step 3:** Definition of criteria and their weights
  - Criteria: goals and objectives of the stakeholder
  - Weights: representing the importance the stakeholders are attaching to the objectives
- **Step 4:** Creation of indicators (evaluation criteria)
  - Definition of the measurement method for each indicator
  - Measurement of the performance of each alternative in terms of its contribution to the objectives of specific stakeholder groups
- **Step 5:** Construction of an evaluation matrix, aggregating each alternative contribution to the objectives of all stakeholders
- **Step 6:** Sensitivity analysis (ranking of the various alternatives and reveals the strengths and weaknesses of the proposed alternatives)
- **Step 7:** Implementation and feedback loop

Steps 1 to 4 can be considered as mainly analytical, and they precede the 'overall analysis', which takes into account the objectives of all stakeholder groups simultaneously and is more 'synthetic' in nature.

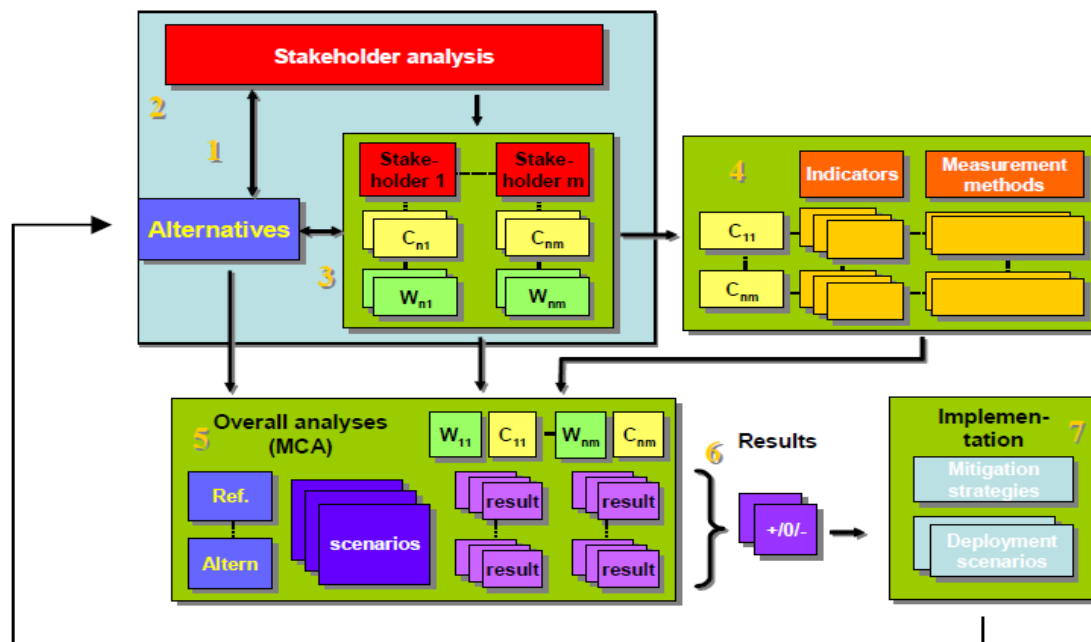


Figure 3. MAMCA methodology (Macharis et al. 2009).

### 5.3.2 MAMCA methodology in AI-CUBE

The seven steps of MAMCA and how they are applied to the AI-CUBE project are described below.

#### Step 1 Scenario building

The process started with the consolidation of trends and potential future AI&BD implementation into 4 scenarios that depict the future of the process industry. These narrative scenarios were built using the intuitive logics method and literature search.

#### Step 2 Identification of stakeholders and their objectives

In the stakeholder analysis, all stakeholder groups that are relevant for the evaluation were mapped and their objectives were identified by the consortium members. The objectives were related to the impacts identified in the AI-CUBE impact matrix and identified with the most voted ones in the online survey.

#### Step 3 Criteria and weights

Each stakeholder attached weights to the criteria that have been derived from objectives related to their own stakeholder group through the online survey. The weighting was assigned according to the votes that each of the impacts obtained in the survey.

#### Step 4 Indicators

The indicators and measurement methods for each criterion were previously identified in the Impact matrix. Indicators are used to measure the performance of a scenario i.e. how important would be a criterion for a future scenario compared to the current situation.

## Step 5 Evaluation by experts

The scenarios have been evaluated by international experts based on qualitative assessment (SMART evaluation from 1 to 10). Therefore, the importance of each criterion (likelihood of the criterion to be met) in each scenario is assessed.

## Step 6-7 Scenario ranking and consensus building

The above methodology is facilitated through an online decision-making platform, i.e. the innovative MAMCA software providing an interactive method to evaluate options and provide easy-to-understand visualizations of the evaluation outcomes.

The MAMCA process developed for AI-CUBE is showed in Figure 4, a complete explanation is included in the next section. The scenarios developed in AI-CUBE, the stakeholders identification, their relation with the criteria and an example of the KPIs for each criterion.

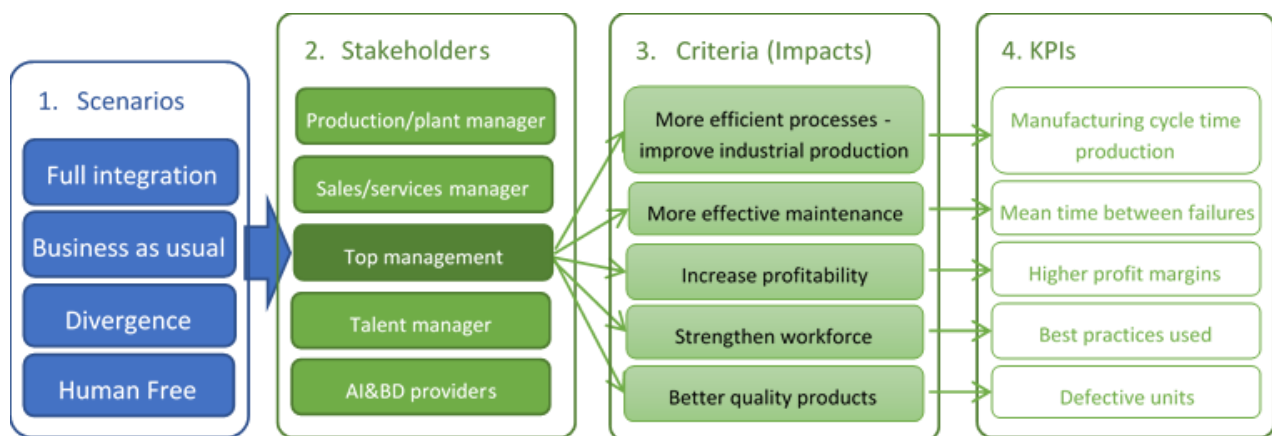


Figure 4. MAMCA process as applied to the AI-CUBE project (this includes just an example of the KPIs considered)

## 5.4 IMPACT ASSESMENT WORKSHOP DESIGN

In addition to providing the framework as to how the MAMCA methodology can be used for impact assessment by different stakeholders, we also tested it through a workshop. A workshop with process industry experts for impact assessment took place in October 2021, which included:

- Definition of the alternatives (scenarios)
- Identification of the stakeholders (actors) and their objectives
- Selection of criteria and KPIs
- Weights of the criteria
- Evaluation

Since MAMCA does not produce an ultimate ranking of the scenarios, the workshop on Impact Assessment also explores the likelihood of such scenarios in regards to the implementation of AI & BD solutions in process industry happening in the future.

#### 5.4. Definition of the alternatives (scenarios)

Each scenario developed in Task 2.3 is based on different assumptions representing diverse possible future development paths of a number of key factors or driving forces. Hence, the scenarios represent a selection of the major trends that influence the implementation of AI&BD technologies and a subset of the technological, organizational, financial and human-related impacts that respond to these trends.

After literature research and internal discussion, the trends are combined into four preliminary scenarios. These preliminary scenarios are not prescriptive; rather they provide a starting ground for discussion.

The two pivotal uncertainties were considered. The first one is the “degree of implementation” in the organization and sector. If the technologies are implemented in all the processes and activities of the organization (scenarios FULL INTEGRATION and HUMAN FREE) or if the implementation is fragmented in the organization or in the sector (BUSINESS AS USUAL and DIVERGENCE). The second uncertainty is related to the type of implementation. The implementation of AI&BD technologies was considered as responsible, taking into account the implication for all whole organization or sector (BUSINESS AS USUAL and FULL INTEGRATION), or unlimited, without any qualm in the impact in the operations, business or workforce for the organization or sector (DIVERGENCE and HUMAN FREE). The scenarios identified in AI-CUBE in relation the uncertainties mentioned above are shown in Figure 5.

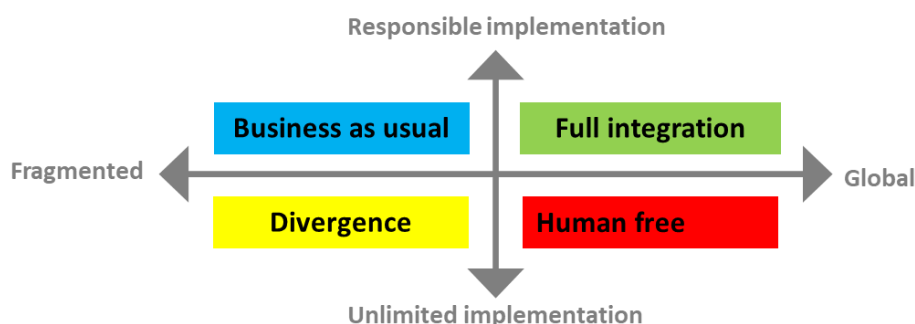


Figure 5. The AI-CUBE future scenarios

Each scenario is described in more detail below:

<b>Full integration</b>	In this scenario AI & BD has evolved and it's integrated in all the departments and processes of the industry. AI & BD helps the operators with dangerous and repetitive work, improving efficiency and optimizing processes, humans can focus on core activities and be more productive. AI and BD help with sales and other services as well as at strategic level, helping with decision making, customer satisfaction and new products design. AI&BD technologies allow the optimization of resource management along the supply chain.
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



<b>Business as usual</b>	AI & BD technology has been slightly introduced in the industry and contributed in a limited way to the organization objectives and the optimization of production, processes and maintenance. Humans are the main resource in the organization. Natural evolution of the industry with time.
<b>Divergence</b>	Low investment in AI&BD technologies lead to a low implementation level in many companies, with only big firms investing in these technologies and displacing small companies from the market, making differences between small and big companies even bigger in terms of competitiveness (potentially leading to “irresponsible” use of AI & BD because of unfair competition, abuse of power by large firms and reduced customer welfare).
<b>Human free</b>	AI has been extensively used in the industry with no control or protective strategy, replacing a large number of workers in industry. Organizations trim head count as a result of AI technologies eliminating humans from organizations. Society segregation (pro AI or against AI). Humans jealous of the attention AI gets.

#### 5.4.2 Identification of the stakeholders (actors) and their objectives

Stakeholders in the MAMCA approach are the actors that have influence on AI & BDA deployment, as well as who would be affected from the widespread use of such solutions. Chen et al. (2015) use the Technology/Organization/Environment framework, and observe that all these aspects, along with Top Management Support, have an impact on how AI & BD solutions affect performance, *asset productivity* (e.g., cash&inventory, fixed assets like plant, equipment) and *business growth* in particular. We also consider different actors in our approach with the MAMCA methodology, and consider the impact of technology providers, human resources, and the top management (particularly related to competitive pressures and dynamism in the business environment) in addition to the more straightforward candidates such as processes related to plant (e.g., production, storage) and customer/demand management in the process industry.

The main relevant actors in the process industry facing the transition to AI and BD technologies were considered. Inside the organizations, the production/plant manager, sales/service manager, talent manager and top managers were identified as relevant actors. From outside the organizations, the AI&BD providers were considered relevant for the transition as specialists in the area and able to drive the implementation of these technologies in the industry. In Table 4 (below) the actors identified and their objective in the industry are indicated.

Table 4. Actors in the process industry

	<b>Production/plant manager</b> Improve production processes/layout and effective maintenance
	<b>Sales/services manager</b> Increase benefits and customer satisfaction
	<b>Talent manager (human dimension)</b> Fulfil workforce requirements and occupational wellbeing
	<b>Top management (organization/strategy)</b> Successful management, planning and future strategy (holistic view)





#### AI&BD technology providers/consultants

Advice and design of best technology application to improve products, services and processes in the industry

We assume all the actors are considered to have the same weight for the evaluation in the context of AI-CUBE project.

## 5.5 SELECTION OF CRITERIA AND KPIS

The MAMCA method relies upon the evaluation of the scenarios using the unique criteria of the stakeholder groups. The ranking of the scenarios reflects the relative importance of these criteria to the stakeholders under different circumstances.

The most voted impacts in the survey (along with the brief definitions) are included in the MAMCA as shown in Table 5 below.

Table 5. Criteria for the evaluation of the scenarios.

<b>Criterion 1</b>	<b>More efficient processes - improve industrial production</b>
	Solutions allow to increase efficiency of production processes in the process industry enabling industries to achieve an improved industrial production
<b>Criterion 2</b>	<b>More effective maintenance</b>
	Solutions aim to reduce the number of equipment failures and increase the productivity and the overall plant lifetime
<b>Criterion 3</b>	<b>Strengthen workforce</b>
	Solutions enforce cooperation between the organization and the operators to build a more effective workforce. Full digitalisation and automatization of the operations at operator level is enabled by organization. Integrated technological applications are part of the company strategy at high level
<b>Criterion 4</b>	<b>Increased profitability</b>
	The solutions are focussed in increasing the business profitability. The focus is on increasing sales and value to the customer and reducing costs through specific solutions
<b>Criterion 5</b>	<b>Better quality products</b>
	Improved quality through reduction of number of defective units

ANNEX I provides information as to how each impact could be measured (alternatively how to verify that each criterion is met) including the criteria and KPIs for their measurement.

### 5.5.2 Weights of the criteria

The criteria, which were derived based on the stakeholder objectives and the impacts identified in the AI-CUBE Impact Matrix previously, were weighed by the stakeholders. The relative importance, i.e. the weight of each criterion, was determined by the online survey. The most voted impacts

aligned with the objectives of the stakeholders, identified as the criteria of the MAMCA approach were weighed according to the number of votes received on a 100% scale as follows:

Table 6. Weights of the criteria.

Criterion	Weight
<b><i>More efficient processes - improve industrial production</i></b>	24%
<b><i>More effective maintenance</i></b>	21%
<b><i>Strengthen workforce</i></b>	21%
<b><i>Increased profitability</i></b>	18%
<b><i>Better quality products</i></b>	18%

### 5.5.3 Criteria evaluation

In the MAMCA, different methods can be used to create the evaluation matrix. Previous MAMCA applications have used the Analytic Hierarchy Process AHP (Turcksin et al. 2011) or PROMETHEE (Preference Ranking Organization Method for Enrichment of Evaluations) (Macharis et al. 2004).

The evaluation can be based both on quantitative and qualitative criteria, and given this context where there are stakeholders coming from different sectors and firms of different sizes, we use qualitative assessment and not focus on real financial/operational data

We applied SMART evaluation on a 10-point scale for the evaluation, available in the MAMCA software. This scale allows us to differentiate between highly important to negligible impacts. The scale indicates the magnitude of the impact without a concrete quantitative meaning.

An online evaluation workshop took place on 8 October 2021 with the participation of 5 experts and the consortium member. Regarding the experts, we count on the participation of 2 experts in AI&BD technologies (identified as providers according to AI-CUBE's classification). The other experts took part in the workshop as users, one of the experts belonged to the water sector, another expert represented the steel sector (project INEVITABLE) and the third expert worked at a technological enter (project CAPRI). The evaluation scores of the 5 criteria were presented one by one to the experts, assuming the roles of different stakeholders, and a discussion followed until an agreement across participants of a certain role was reached. The evaluation for each criterion was finalized based on the consensus at the workshop. Summarizing, 5 external experts (2 AI & BD providers and 3 users) and 5 consortium partners participated in the workshop, all of them played the roles of the stakeholders for the MAMCA evaluation.

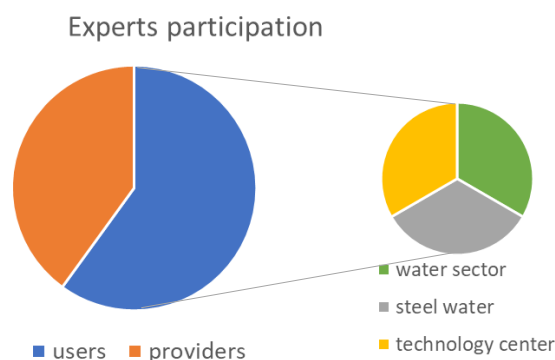


Figure 6. Expert participation in the workshop on impact assessment.

## 6. WORKSHOP RESULTS

With the help of the survey and the workshops, we have identified the perceived benefits (impact) of AI & BD in the process industry. We would like to remind the reader that the impact evaluation results we present in this section are not based on specific financial/operational data, but on the opinion of the industry experts who contributed to the AI-Cube project. Although we were not able to perform a truly quantitative analysis due to the limitations in regards to time and access to real data and strategic nature of this research at a high level (e.g., ideally, data that shows the impact of AI for a particular firm before and after the deployment of a particular AI based solution), we recommend that future work in this area include in-depth analysis of financial/operational data to measure the impact of AI & BDA in firms that deploy such solutions, considering control variables such as the size of the firm, number of products/services offered, sector, etc). This observation will be included in the roadmap definition for the deployment of AI & BD in the process industry in WP4.

### 6.1. WORKSHOP EVALUATION

For the workshop, evaluation tables were created for each actor. The evaluation tables contain information about the specific criteria, scenarios, the indicator(s) that can measure each criterion, and allows the participants to enter a score from 1 to 10 for each criterion per scenario.

During the workshop, the attendees were divided into different breaking rooms to work in the evaluation of the criteria per actor. All the participants joining a specific room were asked to play the role of the desired actors (the selection of the participants in the different breaking rooms was done according to their preferences). Approximately groups of 4 people were created to work together and reach consensus to fill the evaluation table for each actor. Due to the number of participants who attended the workshop, 3 groups were created. One group assumed the role of "Top Management" and "Talent Manager", the second group assumed the roles of "Production/Plant Manager" and "Sales/Services Manager", and finally the third group filled in the tables as "AI&BD Technologies Providers and Consultants".

The final scores (after a consensus is reached within each group following the in-group discussions) per actor are presented below, followed by the main points of the discussion during the workshop.

#### 6.1.1. Top management

SCENARIO	Criterion 1 More efficient processes - improve industrial production	Criterion 2 More effective maintenance	Criterion 3 Strengthen workforce	Criterion 4 Increased profitability	Criterion 5 Better quality products
Full integration	10	10	10	5	10
Business as usual	8	8	8	3	8
Divergence	9	9	9	4	9
Human free	6	6	2	3	6

### Main discussion points during the workshop:

- The attendees pointed out that profitability depends not only on costs, but on many other factors (such as political issues). This is the case in the water sector (one participant was an expert in this sector), where the prices are regulated, and a reduction in costs (because of more efficient production for example) may lead to reduction in prices even, thus no change in profits. The situation might be different for other sectors though. For example, one participant with in-depth knowledge in the metal industry mentioned that firms in this industry have more control over the prices and can increase their profits if they become more efficient (unless competitors also get more efficient and the prices fall for the whole sector).
- Also, some criteria are more relevant than other for different sectors. For example, in the metal sector, Criteria 2 and 5 are more relevant (the quality of the product is crucial to meet the specifications) while Criteria 1 and 2 are more relevant for the water sector as the water quality should be of a certain level with or without the AI & BD deployment.
- Considering the scenario DIVERGENCE, there are big players in the water sector (especially the distributors). These distributors usually control the supply in a whole country and they have access to the most important data at many locations, making easier for them to control small companies. Therefore, it is likely that big players will control smaller ones (or acquire even) and this would likely lead to higher prices for consumers overall and more profits for the big players. The impact on the small players would be the opposite.
- The scenario HUMAN FREE is perceived to be very unlikely. Strong collaboration between humans and machines is still necessary. AI & BD can support decision-making process, but decisions are finally taken by humans. Firms still need human knowledge and judgment to check the information, make sense out of it.

#### 6.1.2. Sales/Service Manager

SCENARIO	Criterion 1 More efficient processes - improve industrial production	Criterion 2 More effective maintenance	Criterion 3 Strengthen workforce	Criterion 4 Increased profitability	Criterion 5 Better quality products
Full integration	9	9	9	8	10
Business as usual	8	8	8	5	8
Divergence	6	8	7	6	8
Human free	6	6	4	5	8

### Main discussion points during the workshop:

- Profitability for all the scenarios was controversial when the attendees evaluated this criterion. Some of them considered this criterion as an important one and some other gave no importance to this. The agreement resulted in values lower than those for the other criteria in general.
- The attendees to the workshop positioned in a different way then evaluating the criteria 3, 4 and 5 in the scenario HUMAN FREE. This disagreement resulted in very different evaluation values for some participants. Strengthen Workforce was evaluated from low to very low, Increased profitability from very low to very high, and Better Quality Products from medium to maximum. Averaged values were agreed for the consensus evaluation.

### 6.1.3. Talent Manager

SCENARIO	Criterion 1 More efficient processes - improve industrial production	Criterion 2 More effective maintenance	Criterion 3 Strengthen workforce	Criterion 4 Increased profitability	Criterion 5 Better quality products
Full integration	10	10	10	7	10
Business as usual	8	8	8	5	8
Divergence	9	9	9	6	9
Human free	3	3	0	5	3

#### Main discussion points during the workshop:

- The participants in this group did not think that the HUMAN FREE scenario is likely to happen. They understand that AI helps the maintenance tasks in water and metal sectors for example, but not replacing workers. On the other side, AI should help organizations to select personnel with better skill sets, , with reduced cost of selection because of faster analysis of curriculum vitae and historical records of potential candidates.

### 6.1.4. Production/Plant Manager

SCENARIO	Criterion 1 More efficient processes - improve industrial production	Criterion 2 More effective maintenance	Criterion 3 Strengthen workforce	Criterion 4 Increased profitability	Criterion 5 Better quality products
Full integration	9	9	9	9	7
Business as usual	7	7	6	6	7
Divergence	7	8	8	6	7
Human free	9	9	4	6	7

#### Main discussion points during the workshop:

- There seemed to be more disagreement for Criterion 3 in this group, for the HUMAN FREE scenario. Some of the attendees gave a high score, arguing that a lower number of people in the organization would result in more concern in their wellbeing, training and skills. Other attendees, however, pointed out the easy replacement of humans by machines that would provide less incentive to invest in strengthening the workforce.

#### 6.1.5. AI&BD providers

SCENARIO	Criterion 1 More efficient processes - improve industrial production	Criterion 2 More effective maintenance	Criterion 3 Strengthen workforce	Criterion 4 Increased profitability	Criterion 5 Better quality products
Full integration	9	9	8	9	9
Business as usual	7	7	9	7	7
Divergence	8	8	7	8	8
Human free	9	9	1	10	8

#### Main discussion points during the workshop:

- Size of company harms the ability to take on-board AI, one AI&BD provider was of the opinion that this was not such a problem as small companies can access public funding, for example, for innovation actions. However, another provider had a slightly different opinion that small companies could trail behind due to lack of time/resources, etc.
- The attendees agreed that substituting all (or the majority) of humans is not a good idea (when “human free scenario” is considered), even if it implies optimum productivity. So, automation should replace tasks not apt for humans (dangerous, repetitive, etc.), help humans to do a better job, make work conditions better, etc.
- It was mentioned that control and monitoring and predictive maintenance (criteria 1 and 2) are key topics for process industries.
- AI&BD providers mentioned that some companies want to jump to AI&BD when they still don't have integrated IT systems or databases, and therefore the need to address those issues first (digitalization). Other provider pointed out that in other cases companies just want to use AI as marketing and what they implement may be something much simpler.
- Criteria 4 and 5 seemed quite relevant and there was consensus within the group.

## 6.2. MAMCA ANALYSIS

The results of the evaluation, generated by the MAMCA software in the form of the ranking of scenarios for each stakeholder group (step 6) are presented in this section. The overall result of the MAMCA analysis is shown in Figure 7. Remember that for the evaluation, the participants were asked about how likely they thought each criterion would be met in each scenario. (The detailed sensitivity analysis per actor is represented in Annex II).

According to the joint assessment of all the stakeholders, the scenario FULL INTEGRATION would almost ensure that all the criteria be met with much certainty. BUSINESS AS USUAL and DIVERGENCE scenarios seem to have similar impact on the criteria (the relevance of different criteria seem to be uniform), with the DIVERGENCE scenario leading to slightly higher likelihood of the criteria to be met. One possible explanation of the DIVERGENCE scenario leading to higher scores might stem from the observation that bigger firms might significantly benefit from AI & BD, potentially displacing the smaller firms, resulting in an overall improvement for the industry as a whole. The FREE HUMAN scenario seems to have the lowest scores, as participants believe that the human element is actually crucial for improving financial/operational performance of the firms, and therefore the likelihood of the criteria being met are rather low (even if one assumes this

scenario happens in the future). As expected, the scores of top management and talent management are lower on average.

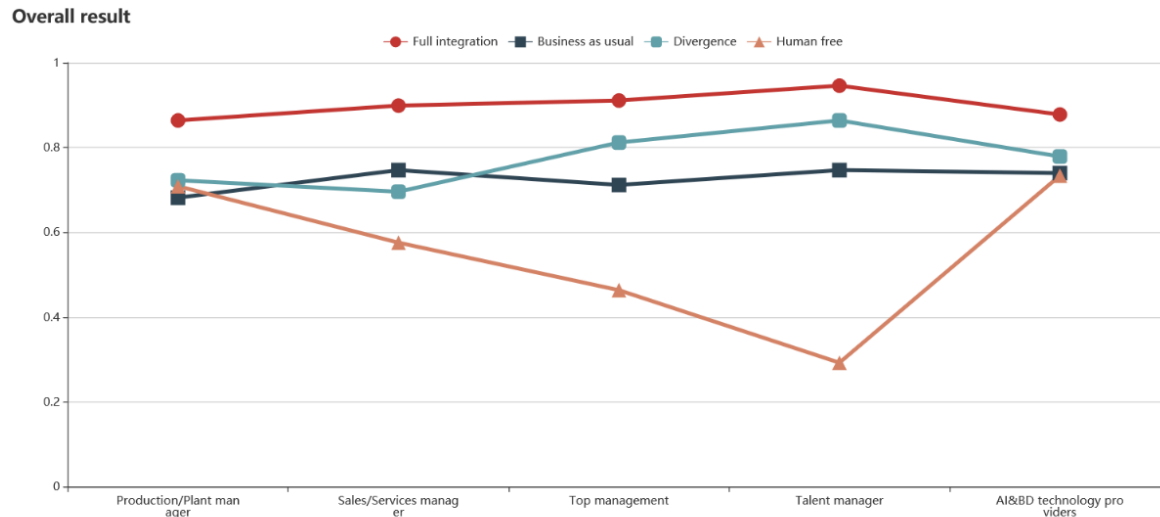


Figure 7. Overall result of the MAMCA analysis.

After analyzing the scenarios evaluation per actor, we observe that some impacts are highly evaluated in all the scenarios, namely criteria 1, 2, and 5. The scenario HUMAN FREE gives different evaluation to all of the criteria reducing significantly the values. So, we can conclude that from our preliminary prioritization of the impacts (from the results of the online survey) all the impacts have High importance (ranked from 6 to 8) and one impact (More effective maintenance) has Very high importance (from 8 to 10) for the future of the AI & BD technology in the process industry as indicated in Table 7:

Table 7. Final impact evaluation per actor.

Criteria	Importance	Top management	Production /Plant	Sales/ Services	Talent manager	AI&BD provider
More efficient processes - improve industrial production	High – 7.8	8	8	7.25	7.5	8.25
More effective maintenance	Very high - 8	8.25	8.25	7.75	7.5	8.25
Strengthen workforce	High – 6.75	7.25	6.75	7	6.75	6
Increased profitability	High - 6.15	3.75	6.75	6	5.75	8.5
Better quality products	High – 7.95	7.85	7	8.5	7.5	8

The scores for more efficient processes, more effective maintenance, and better-quality products are quite high for different actors across different scenarios. This result is somewhat in keeping with the focus of the process industry on such criteria in general. However, there seems to be a



higher level of uncertainty in regards to the impact of AI & BD on profitability under most scenarios, compared to other criteria. The average scores are appreciably lower for this criterion (increased profitability). Top Management seems to be particularly unsure about the impact on profits. This is an interesting result as the other actors (production/plant, sales, AI & BD provider in general) seem to be more optimistic about the potential impact of AI & BD on creating more efficient processes, more effective maintenance and better-quality products. But, these do not seem to directly translate into higher profits, even to a lesser extent from the perspective of top management. Although it is desirable to have more efficient and effective processes, as the ultimate goal of any for-profit organization is to make more money, this result indicates to a potential lack of willingness to invest in AI & BD deployment by top management. The relationship between the increased profitability and other criteria must be analysed in more depth in order to identify what is causing this ambiguity in order to promote AI & BD in process industry.

### 6.3. TIMELINE – FUTURE PERSPECTIVE OF AI&BD IN THE INDUSTRY

In order to understand which scenarios are more likely to happen in the near future, all participants were encouraged to share their opinions at the end of the workshop. It seems like the scenario DIVERGENCE is expected to become a reality within the next 5-10 years since big companies are already investing in AI&BD technologies while small companies are not, especially in the water sector. In the medium term within 20 years from now approximately, however, the sector expects a FULL INTEGRATION scenario where AI & BD applications are completely integrated in all the organizations of the sector at all levels, due to the inclusion of small companies in the big ones or their disappearance from the market.

AI&BD providers pointed out that there is hope for small companies since AI&BD applications will become a commodity, present in all industries, like chips, little devices and software applications, which could enable the use of AI&BD technology at all levels.

In conclusion, the integration of AI&BD integration in the short term (by 2025) seems very complicated as pictured in the scenario FULL INTEGRATION. There are significant challenges in data centralization, integration, and verification in the industrial plants before starting integrating mathematical models required by AI and BDA. In line with the “garbage in, garbage out” principle, if wrong data is integrated, the model will be wrong. The industry experts seem optimistic though, that within approximately 10 years, these barriers would be overcome and process industry would be benefiting from AI & BD, similar to the benefits other high-tech industries are currently enjoying.



## 7. CONCLUSIONS

Despite the hype around the promise of AI & BD, firms need to carry out a careful and detailed analysis of the costs involved in the deployment of these technologies/solutions and the potential impact. This is necessary to determine if the return on investment will be sufficiently high to warrant the significant investments to be made to deploy AI & BD (in the order of millions of dollars in many cases, for owning and operating such systems).

Although there is some research on how to measure and quantify the impact of AI & BD and similar technologies/solutions in the literature, we conclude (based on the review of the relevant literature) that the financial, operational, social, and environmental impact of such solutions is quite difficult to measure and quantify in general. The situation is especially complicated in the process industry, where the adaption rate of such technologies is somewhat slower, and mostly limited to production control and maintenance activities, compared to some other industries. This leads to the observation that decision makers usually go for such investment based on “perceived” benefits due to the limited empirical evidence proving the benefits of AI & BD in process industry for the time being. In Section 4 of this deliverable, we provide some examples as well as figures in regards to the potential impact. The AI & BD seems to not only have positive financial effect (e.g., increased sales, higher profit margins), but also has an impact on operational performance (e.g., higher productivity, longer equipment life cycles), social aspect (e.g., labor safety), and environmental performance indicators (e.g., improved waste collection/management). All in all, the deployment of AI & BD seems to be promising in the medium to long term.

In order to promote the use of AI & BD in the process industry, we focus our efforts on the development of a framework to be able to measure the impact. An impact matrix with 20 impact factors has been created, based on the A.SPIRE positioning paper (which lists the potential impact to be expected in the process industry) and the desk research. An important issue here is to make sure that the number of impacts and the indicators (KPIs used to measure the associated impact) is kept at acceptable levels, not to burden decision makers with the demanding task of collection of data and measurement of too many KPIs. Therefore, through consultations with the industry experts and an online survey, we further reduced the size of the impact matrix, and only worked with 5 such factors (the most voted ones). The most voted impacts were: (1) More efficient processes - improve industrial production, (2) More effective maintenance, (3) Strengthen workforce, (4) Increased profitability, and (5) Better quality products.

In order to understand how different stakeholders value AI & BD, we employ the MAMCA methodology. The scenarios (Full Integration, Business as Usual, Divergence, and Human Free) in relation to the adaption rates and the manner AI & BD solutions are deployed in the future and the actors (Production/Plant Manager, Sales/Services Manager, Talent Manager, Top Management, and AI & BD Technology Providers/Consultants) are defined in this methodology. We also present the criteria (the 5 impact indicators mentioned in the previous paragraph) and the associated KPIs to aid in impact evaluation. This deliverable therefore provides a practical and reasonably detailed decision support tool that would help managers make informed decisions in regards to impact evaluation under different scenarios.

We also pilot-test this methodology with a number of industry experts in the process industry via a workshop. We observe that this pilot test of the methodology is quite effective in facilitating a discussion leading to a more objective evaluation of impact of AI&BD technologies in the process industry. In addition to the numerical scores in relation to the potential impact, we also obtained some useful managerial insight during the workshop. In Section 5, we present easy-to-understand

visualizations of the evaluation outcomes. All 5 impacts were confirmed as important/very important to all the stakeholders, in almost all scenarios. The lowest score (although still high) was for “increased profitability” as it was not very clear how to connect the associated operational benefits to the profits in the end and the fact profits are regulated by many other factors (e.g., political). The results are positive therefore, and point to a certain level of willingness to deploy AI & BD in process industry.

We also aim to understand through the MAMCA, whether these stakeholders agree on the impact or they have opposing views as to how the industry will be affected, which would eventually either foster joint efforts in deploying such solutions or impede. There are some differences in terms of how different actors evaluate the impact (e.g., plant manager focusing more on effective process), but we did not observe stark differences that would deter companies from making investments in AI & BD solutions.

We also received feedback in terms of the likelihood of these different scenarios happening in the medium to long term, and potential impact and cost of deployment. Except for the “Human Free” scenario, the other scenarios are likely to happen based on our results. Participants were optimistic in the sense that machines will not replace humans, they will simply amplify the human potential, which we think is good news for the society at large.

Last but not least, we would like to remind the reader that, although our results are representative of the overall sentiment of the process industry towards the deployment of AI & BD, our research is limited by the rather low response rate to the survey and the workshop. Future pilot tests of this approach must be carried out with more participants, in order to reach more statistically significant results. Nevertheless, the results of this deliverable will be an input to the roadmap design in WP 4 for the SPIRE community specifically and the process industry at large.

## 8. BIBLIOGRAPHY / REFERENCES

A.SPIRE PAPER. ARTIFICIAL INTELLIGENCE in EU PROCESS INDUSTRY A VIEW FROM THE SPIRE cPPP. 2019

(<file:///C:/Users/AMARTI~1/AppData/Local/Temp/ASPIRE%20AI%20PROCESS%20INDUSTRY%20POSITION%20PAPER.pdf>)

Brynjolfsson, E., Hitt, L. M., Kim, H. H. (2011). Strength in numbers: How does data-driven decision-making affect firm performance?. Technical report. April 22, 2011. [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1819486](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1819486)

Chen, D. Q., Preston, D. S., Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems*. 32 (4), pp. 4 – 39.

Dumitrscu, O., Dumitrascu, M., Dobrota, D. (2020). Performance evaluation for a sustainable supply chain management system in the automotive industry using artificial intelligence. *Processes*. 8, p. 1384.

Hummel, Marjan & Bridges, John & IJzerman, Maarten. (2014). Group Decision Making with the Analytic Hierarchy Process in Benefit-Risk Assessment: A Tutorial. *The patient*. 7. 10.1007/s40271-014-0050-7.

Kamble, S. S., Gunasekaran, A. (2020). Big data-driven supply chain performance measurement system: a review and framework for implementation. *International Journal of Production Research*. 58 (1), pp. 65 – 86.

Lee, H. L., Blake, L., Mendelson, H., Rammohan, S. (2018). Value Chain Innovation: The promise of AI. Stanford Graduate Business School White Paper. October 2018.

Macharis, C., Springael, J., De Brucker, K., & Verbeke, A. (2004). PROMETHEE and AHP: The design of operational synergies in multicriteria analysis.: Strengthening PROMETHEE with ideas of AHP. *European Journal of Operational Research*, 153(2), 307–317. [https://doi.org/10.1016/S0377-2217\(03\)00153-X](https://doi.org/10.1016/S0377-2217(03)00153-X).

Macharis, Cathy & Witte, Astrid & Ampe, Jeroen. (2009). The Multi-Actor, Multi-Criteria Analysis Methodology (MAMCA) for the Evaluation of Transport Projects: Theory and Practice. *Journal of Advanced Transportation*. 43. 183 - 202. 10.1002/atr.5670430206.

Manecke, N., Schoensleben, P. (2004). Cost and benefit of internet-based support of business processes. *International Journal of Production Economics*. 87, pp. 213- 229.

Müller, O., Fay, M., Vam Brocke, J. (2018). The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics. *Journal of Management Information Systems*. 35 (2), pp. 488 – 509.

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*. 122, pp. 502 – 517.

Turcksin, L., Macharis, C., Lebeau, K., Boureima, F., Van Mierlo, J., Bram, S., ... Pelkmans, L. (2011). A multi-actor multi-criteria framework to assess the stakeholder support for different biofuel

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options: The case of Belgium. Energy Policy, 39(1), 200–214.  
<https://doi.org/10.1016/j.enpol.2010.09.033>.

## 9. ANNEXES

### ANNEX I – CRITERIA AND KPIS FOR THE SCENARIOS EVALUATION

Table 8. Criteria and KPIs for the evaluation of the scenarios.

Criterion 1	Indicators	KPI
<b>More efficient processes - improve industrial production</b>	Less rework and higher yield as a result of increase in first-time-right production	First-time-right production
	Reduction in the manufacturing cycle time due to increased production rate (leading to increased yield)	Manufacturing cycle time
	Improved Overall Operating Efficiency (OOE), with better performance, quality, and availability of operating time	Overall Operating Efficiency (OOE)
	Improved Overall Equipment Effectiveness (OEE), with better performance, quality, and availability of scheduled time	Overall Equipment Effectiveness (OEE)
	Improved Scheduling, Monitoring and Process Management and therefore better adherence to schedule (less "behind plan" and improved schedule compliance)	Adherence to schedule
	Supervised autonomous plants, self-organization of industrial production, and use of real-time digital-twin simulation for frequent optimization of operations	Operation optimized
Criterion 2	Indicators	KPI
<b>More effective maintenance</b>	AI augmented supervision of maintenance routines and component spare parts replacement reducing equipment/plant downtime	Maintenance routines
	Predictive and Planned Maintenance increasing the "Mean Time Between Failures"	Mean time between failures
Criterion 3	Indicators	KPI
<b>Strengthen workforce</b>	Increased number of high quality/interpretable/accessible reports with relevant/useful information generated by AI&BD tools	Useful reports
	A larger "number of processes" across different departments/SC entities utilizing AI&BD generated information	Informed processes
	Increased percent of time decisions informed by AI&BD generated information (automated or human/automated mix)	Informed decisions
	Increased number of "best practices" aided by AI&BD technologies	Best practices used
	Accelerated human/operators learning (i.e., reduced time to proficiency) via more efficient and formalized transfer of operators' knowledge and best practices	Accelerated learning
	Providing scope to gain new/better insights via simplifying human-machine interface with complex processes	Simpler human machine interface
	Improved process for the evaluation of workforce performance (e.g., ability to better monitor KPIs, deviation from targets/objectives, employee/manager feedback, improved employee satisfaction due to more fair evaluation)	Workforce performances evaluation

		Processes improved
	Increased use of AI&BD supported tools for innovation training and R&D	Supported tools used
<b>Criterion 4</b>	<b>Indicators</b>	<b>KPI</b>
<b>Increased profitability</b>	Higher profit margins because of increased value to the customer (larger revenues collected thanks to personalized/customisable product and service offerings)	Higher profit margins
	Higher sales thanks to improved marketing campaigns, better customer segmentation, and faster new product introduction	Higher sales
	Cost reduction (manufacturing, delivery, design, input materials, etc.)	Cost reduction
<b>Criterion 5</b>	<b>Indicators</b>	<b>KPI</b>
<b>Better quality products</b>	Improved quality through reduction of number of defective units	Defective units

## ANNEX II – MAMCA SENSITIVE ANALYSIS PER ACTOR

MAMCA sensitive analysis per actor:

Actor sensitivity analysis: Production/Plant manager

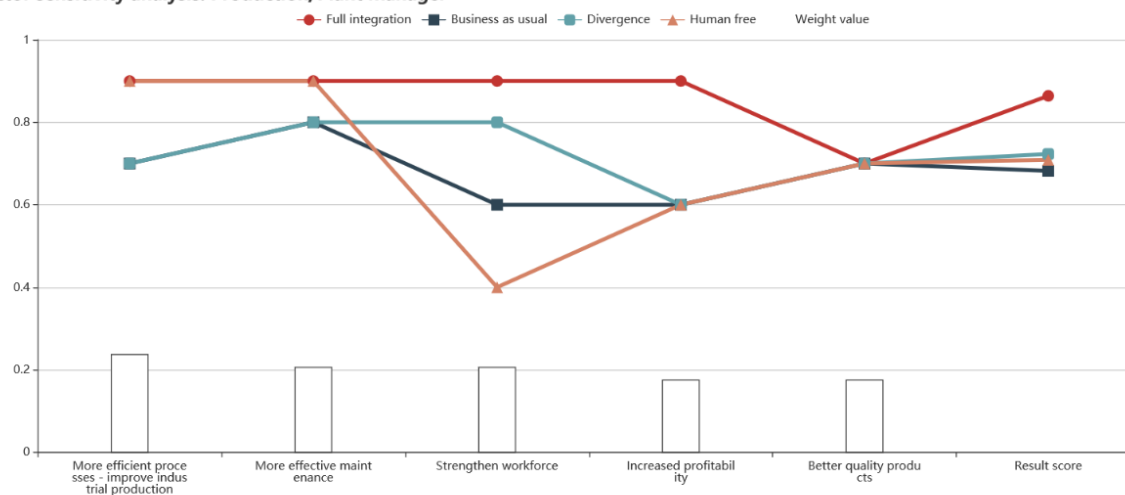


Figure 8. MAMCA sensitive analysis for Production/Plant manager

#### Actor sensitivity analysis: Sales/Services manager

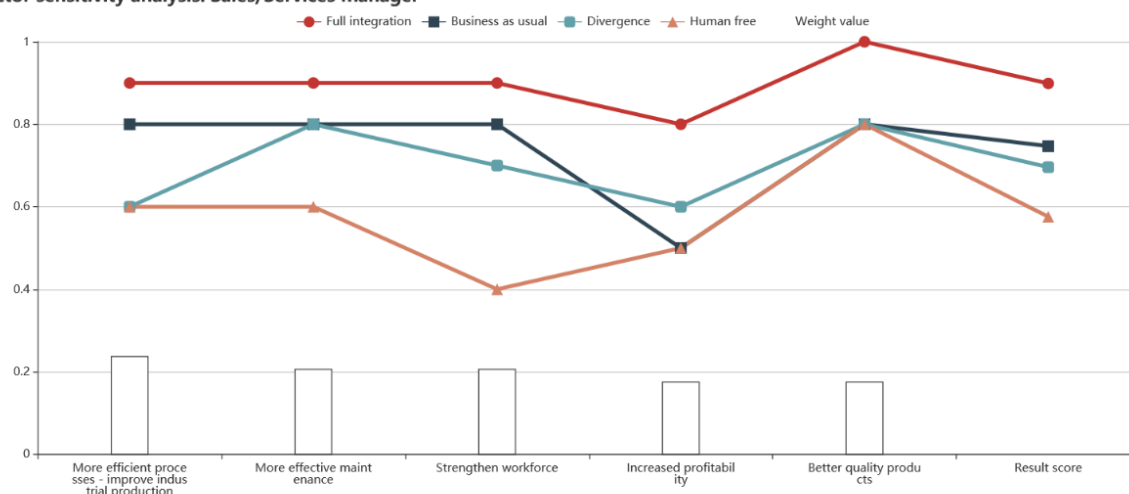


Figure 9. MAMCA sensitive analysis for Sales/Services manager

#### Actor sensitivity analysis: Talent manager

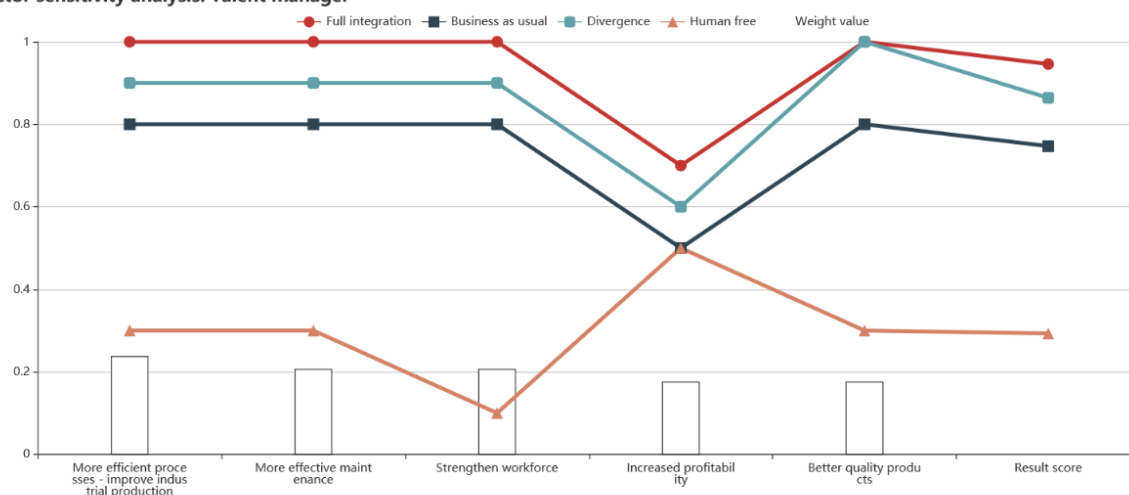


Figure 10. MAMCA sensitive analysis for Talent manager.

#### Actor sensitivity analysis: Top management

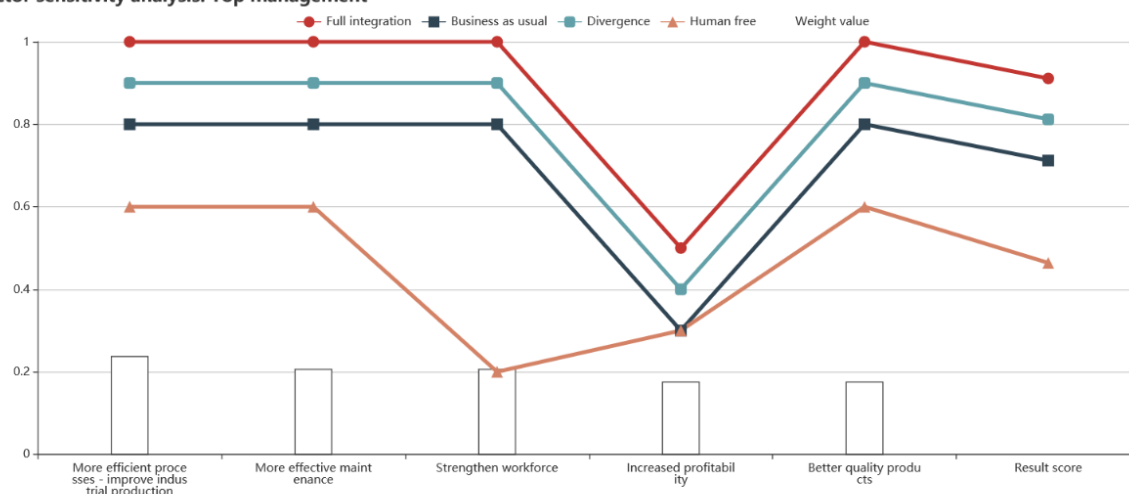


Figure 11. MAMCA sensitive analysis for Top management.

#### Actor sensitivity analysis: AI&BD technology providers

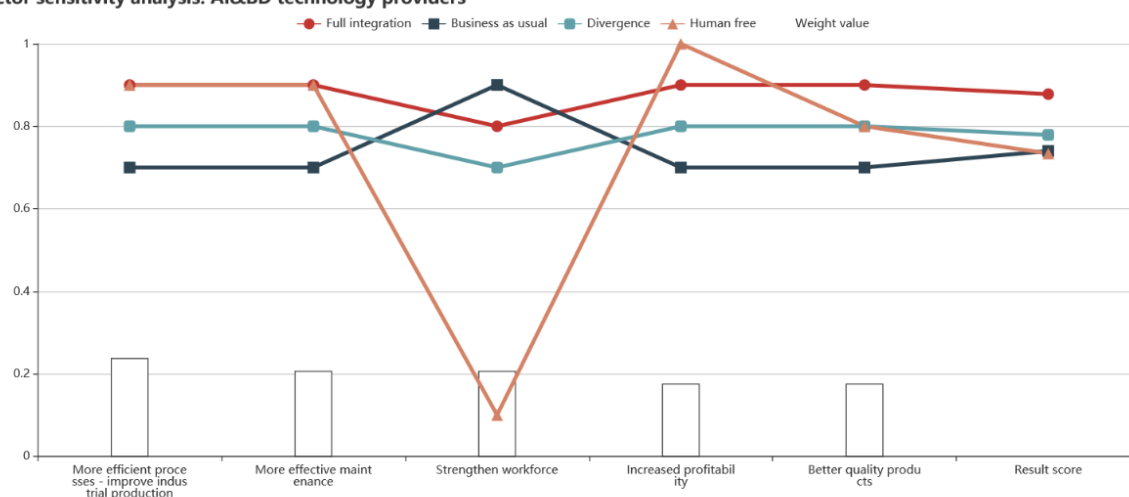


Figure 12. MAMCA sensitive analysis for AI&BD providers.