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Proposing a maturity model for assessing Artificial Intelligence and Big data in the process industry

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ABSTRACT
Among digital technologies, Artificial Intelligence (AI) and Big Data (BD) have proven capability to support different processes, mainly in discrete manufacturing. Despite a number of AI and BD solutions and applications, no comprehensive assessment of their implementation is available for the Process Industry (i.e. cement, chemical and steel) and it is getting urgent to take into consideration specific operations. Grounding on literature and focus group interaction, this paper contributes to answering this gap by proposing a maturity model (MM) for AI and BD and assessing the current status of the application of these solutions in the process industry. Based on MMs available in the literature, a set of dimensions for the process industry has been identified and contextualised for assessing the level of maturity for AI and BD solutions. Results from applying the MM to a sample of European companies reveal that operations are supported by a relatively high level of maturity of AI and BD implementation with differences in the specific dimensions and operations where it is still necessary to invest. The MM can be used by companies both to self-assess and to benchmark with companies from the same or other sectors.

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Introduction

The European Process Industry, through the support of A.SPIRE association is in the peculiear moment to speed-up and harmonise progress in digital transformation, with the application of artificial intelligence (AI) and big data (BD) technologies across the different process industry, from chemicals to steel, cement, and ceramics, up to water and engineering. AI and BD technologies are developing fast, but in a fragmented and diverse manner throughout the different process industries sectors and across different organisational functions and processes within the companies. These technologies are currently being developed and deployed separately, at different maturity levels between different process industries and organisational functions. This represents both a challenge and an opportunity for the European process industry. This a challenge because the benefits of AI and BD solutions to optimise the process industry are not equally being realised in all the process industry sectors, or processes. At the same time, this also offers an opportunity, as positive experiences with AI and BD in one process industry sector can be adapted and transferred to another, once it has become clear what their benefits are and how further development towards AI and BD business cases can be pursued (SPIRE 2050 Vision).

In recent years, AI and BD have enabled firms to increase their profits, and 85% of business leaders believe these technologies will make their businesses remain competitive. At the same time, adoption rates are still quite low; only around 23% implement a kind of AI and BD solution, and a mere 5% have extensively deployed AI and BD solutions, mostly in support functions such as IT and customer service (Ransbotham et al. 2017; Spring, Faulconbridge, and Sarwar 2022). Nonetheless, 77% of industry managers considered machine learning to be the most useful, with smart robotics second (44%) and natural language processing third (40%) (EY 2019). For what concerns BD, the volume of digital data generated from different sources in industrial contexts is increasing by enlarging the number of users, sensors, processes and other sources. Accordingly, the application of this new trend of BD is studied in terms of some examples of applications, such as spatio-temporal data, real-time data, or open data (Radanliev and De Roure 2023).

The process industry generates a vast amount of data and is one of the predestined industrial sectors to apply AI and BD solutions. Still, it is facing the challenge of integrating and defining data structures and interfaces to create access over operations and locations for usage at operational as well as strategic levels by means of AI

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and BD. In the process industry, gathering available data furthermore causes a constraint due to the continuous flow of products (and related information) in order to suitably apply AI and BD. Additional constraints exist in monitoring and handling related data (Mao et al. 2019).

In the literature, several papers demonstrate that in companies of discrete manufacturing (like automotive, fashion and machinery), AI and BD technologies can improve performance in terms of efficiency, sustainability, flexibility, agility, and therewith support robustness and resilience (Arinez et al. 2020; Chien et al. 2020; Manimuthu et al. 2022; Stark et al. 2023) and also systemic approaches and policies are studied (Radanliev et al. 2021). In the case of the process industry, the application of AI and BD is lagging behind given the type of operations – continuous flows can have different problems in terms of monitoring and control with respect to discrete production – both at the product and operational levels and only recently, the process industry has started to adopt these technologies.

After a few years from the start of the Industry 4.0 age, it became evident that implementing digital technologies to support production operations is not only a matter of technological development. Instead, related organisational changes have been studied, too (Nayernia, Bahemia, and Papagiannidis 2022). In particular, AI and BD require interactions between humans, humans and machines, and machine-to-machine. The assessment of strategic and organisational challenges needs to be considered complementary to any technological change (Tortorella et al. 2023). For example, AI converts typical production resources such as workers, machines, and material flows into smart elements to be connected and to exchange information. Another challenge arises when considering BD as the basis for AI since BD needs to be based on appropriate data collection and extraction to provide useful business insights to companies in the decision-making process. Moreover, when creating new collaborative mechanisms with supply chain partners, like using machine-learning techniques with simulation and digital twins, data from each entity in the supply chain is required to be interoperable (Cannas et al. 2024; Pessot et al. 2023). These include, for example, systems for planning data for future parts production, delivery schedules, transport options and lead times, amongst other data sets (Sardesai and Klingebiel 2023). The data handled by these solutions will generate issues regarding privacy concerns. Companies need to take into consideration all the different types of interactions that are enabled by AI within as well as external to their plant (Ogbuke et al. 2022; Pessot, Zangiacomi, and Fornasiero 2024).

Maturity models (MM) can be used to analyse a company's readiness to implement a certain technology. This has proven to be an important instrument to support positioning organisations in a specific comparative framework (Becker, Knackstedt, and Pöppelbuß 2009). By helping to define roadmaps for change, these models help industrial sectors overcome challenges to achieve a winning roadmap for digital transformation (Gökalp and Martinez 2022). MMs can be considered 'multi-stage models that describe typical patterns in the development of organisational capabilities' (Comuzzi and Patel 2016). For each maturity level, the MM describes the corresponding stages for relevant domains. These stages should be logically connected and generalisable to identify the correct maturity level of an organisation or a sector (Hausladen and Schosser 2020). It has become a well-established assessment tool in the area of digitalisation to support the management in complex and novel technology transformation processes (Hausladen and Schosser 2020) and to understand the gaps in the development paths.

While several approaches towards MM for digital technologies in industrial use cases already exist (Nayernia, Bahemia, and Papagiannidis 2022), types of dimensions in an MM for evaluating AI and BD in the process industry remain open. To respond to these gaps, this paper contributes to the literature by designing a framework based on maturity assessment and evaluating the level of implementation of AI and BD solutions in the process industry. Moreover, the paper builds upon the previous studies in order to structure the most important dimensions when dealing with the application of AI and BD solutions, giving relevance to dimensions such as people and ethics which are usually discarded. From the practical point of view, this paper helps to emphasise the organisational advantages of applying an MM that gives the possibility to assess the AI and BD solutions as they are applied in specific operational phases like design, production control, and maintenance (Nayernia, Bahemia, and Papagiannidis 2022; Bibby and Dehe 2018). Thus, this paper answers to the following research questions:

> RQ1. How to structure a framework of a MM for the process industry?
>
> RQ2. How can the MM enable a self-assessment of the maturity level of a company and benchmarking it with others?

This paper is structured as follows: Section 2 provides an overview of the existing MMs and methodologies already available to support the assessment of digital technologies implementation, taking into consideration models assessing digitalisation degrees with a focus on applying AI and BD technologies independently from the application sector. From the results of the literature review, the paper in Section 3 clusters the most important dimensions with the support of experts resulting in Section 4 that selects the most appropriate dimensions and sub-dimensions for assessing AI and BD implementations in the process industry. Moreover, the levels of maturity for each dimension are also described. In Section 5, the MM is structured as a questionnaire for self-assessment addressing two specific categories of respondents: AI and BD users as applicants of the technology as well as the AI and BD providers as implementers of the solutions. In Section 6 the MM is tested and validated with a set of companies from the process industry. The results from collected questionnaires are aggregated and analysed to quantify the AI and BD maturity levels and to analyse and discuss the results providing first theoretical and managerial insights. Section 7 discusses the results and points out their practical impacts on the companies. Finally, Section 8 addresses concluding remarks and opportunities for future research.

Literature review on maturity models

The literature on MMs for digital transformation is manifold and applied to different production contexts. The MMs considered in this paper are related to the implementation of Industry 4.0 technologies with a focus on AI and BD solutions as well as specific digital technologies and industry sectors. Some scientific works are related to the theoretical analysis and literature review of different MMs (Al-Sai, Abdullah, and Husin 2019; Arunachalam, Kumar, and Kawalek 2018; Sadiq et al. 2021; Schumacher, Erol, and Sihn 2016), other works propose new MMs where technologies are mapped to specific processes (Chen et al. 2022; Colangelo et al. 2022) and validated with support of experts (Chen et al. 2022; Wagire et al. 2021) or analyse maturity levels in different domains related to a specific industrial sector (Gajdzik 2022). Yet, there are still few empirical studies showing the organisational advantages of applying an MM linking it to specific operational phases like design, production control, and maintenance (Nayernia, Bahemia, and Papagiannidis 2022; Bibby and Dehe 2018). The analysis in this section aims at identifying dimensions and levels of maturity applied in previous studies.

In particular, to define the characteristics of MMs, Sadiq et al. (2021) review the state-of-the-art related to AI maturity models. They show that MM development typically uses a design approach which is bottom-up, and most models have a descriptive approach. The critical success factors identified by this study are Data, Analytics, Technology and Tools, Intelligent Automation, Governance, People, and Organization. The paper emphasises the criticality of empirical models based on qualitative and quantitative measurements. The authors emphasise the importance of using MMs for AI across various organisations, particularly for benchmarking AI capabilities. Al-Sai, Abdullah, and Husin (2019) analyse MMs for BD in the literature, taking into consideration practical and academic fields. They discuss the principal models deriving from Big Data MM by Halper and Krishnan (2013), Big Data Business Model Maturity Index (BDBMMI) by Schmarzo (2013), IDC MaturityScapes by Vesset et al. (2013), and Big Data MM (BDMM).

There are papers investigating general aspects of Industry 4.0 implementation, including AI and BD, shedding light on the necessity of including different organisational aspects to have a holistic way of assessment. The critical aspects are appropriate roadmaps, analysis of resources, and awareness of such models (Schumacher, Erol, and Sihn 2016). MMs are proved to be one of the practical tools for developing roadmaps by analysing companies beyond the process management aspects (Nayernia, Bahemia, and Papagiannidis 2022). Defining suitable strategies and utilising the correct technologies improves productivity, processes' flexibility, and added value of the related products or services (Stark et al. 2023). These technologies, combined with green initiatives, enhance market quality and personalisation, speed up and optimise operations (Gajdzik 2022).

Wagire et al. (2021) propose an Industry 4.0 MM with BD as one of its major components, which is empirically grounded and technology-focused for assessing the maturity level of Indian manufacturing organisations. Their model comprises 7 dimensions and 38 maturity items derived from experts' opinions. The assessment shows that the '*Product and Services oriented Technology*' dimension has the lowest maturity score while '*Industry 4.0 awareness*', '*People and culture*' and '*Smart Manufacturing Technology*' are the dimensions with moderately high scores. In Pringle and Zoller (2018), the MM for AI is based on five core dimensions: '*strategy*' to assess the state and nature of an organisation's plan of action and alignment with KPIs to support AI, '*organisation*' to assess how much a company is culturally and organisationally ready to support AI in terms of structure, skills, and education on business transformation, '*data*' to assess the state, availability, and governance of data assets and its analytics capabilities, '*technology*', and '*operations*'. The role of developing MMs for the above domains is driven by the customers' demands and should be encouraged by their impacts on the overall strategy of the company personalisation, problem-solving, and customer-centric through providing new digital offerings.

Alsheibani, Cheung, and Messom (2019) develop MM for AI providing insights into the successful evolution and adoption of AI. Four dimensions have been identified: '*AI functions*' referring to the tools and technologies that are required to handle AI at scale, '*data structure*' for the amount and structure of the data to get AI systems to work by enabling high-velocity capture, discovery or analysis, '*people*' to consider individuals within an organisation to create AI technologies and '*organisational*' to include business characteristics and resources that might influence the firm size, managerial structure, decision-making and communication. Gentsch (2019) emphasises the fundamental role of data, algorithms, and AI in the transformation of the company from a non-algorithmic to a semi-automated enterprise, which plays a crucial role in creating new business processes. In this study, five dimensions have been selected, namely '*strategy*', '*people*', '*decisions*', '*data*', and '*analytics*'. It is argued that the competitive advantage that companies gain by moving from a classical strategy and organisational approaches to higher maturity levels is the data- and analytics-driven real-time decision-making. A super-intelligent company should balance the loss of human control of the processes and interfering in the system decisions to make effective corrective actions. Also, Element AI (2020) lists five key dimensions in a similar manner: '*strategy*', '*data*', '*technology*', '*people*', and '*governance*'.

To respond to the literature gap of vague links between AI technology, AI usage and organisational performance, Yablonsky 2021 proposes a multidimensional AI-driven enterprise platform, facilitating the integration between AI business strategy, business processes, and technological frameworks. The advantage of this platform is the adoptability with various platform data from new sources, which results in the valorisation of BD assets. From the organisational point of view, this approach reduces costs and increases competitive advantage. Lichtenthaler (2020) proposes a conceptual framework with three elements to construct the five levels of maturity to manage AI in a company and help to recognise the managerial challenges and significant resource limitations of organisations. The three elements are specifically linked to AI implementation through '*various types of AI*', '*human intelligence*', and the '*meta-intelligence*' to guarantee that the final architecture is more than the aggregate of the different types of intelligence. This framework was built on the grasp of intelligence architecture based on the concept of integrated intelligence and the intelligence-based view of company performance.

The research in BD maturity analysis in the last decade has changed from focusing on data mining to a more holistic view of data: digital innovation and automated systems (Sahoo 2022). Comuzzi and Patel (2016) assess how large organisations leverage BD technologies in their businesses. Through the validation by domain experts, they emphasise the role of governance, sponsorships, and security. BD analytics capabilities in the supply chain lack an analysis from a holistic approach, where integration from heterogeneous data sources and data-driven culture is fundamental for a suitable interaction between people and technologies. In this direction, Arunachalam, Kumar, and Kawalek (2018) developed a framework for the supply chain considering the two pillars:1. '*data generation, integration, and management capabilities*', and 2. '*analytics and visualisation capabilities*'. Consequently, their MM of BD analytics in the supply chain considers the measurement dimensions and stages of maturity. The leaders in BD analytics practice are the ones with high capabilities who fully integrate their processes in the routinisation stage.

In production and operations management, the hurdles of AI applications can be associated with high investment costs, lack of knowledge management, resistance to change, and challenges in data quality. By overcoming these barriers, AI practices positively impact all layers of the value chain, from provisioning to delivering, and result in improvements in cost, service level, quality, safety, and sustainability (Cannas et al. 2024). Colangelo et al. 2022 analyse the maturity of production planning and control, focusing on the applications and roadmaps in Germany and Hungary. They show that more than half of the analysed enterprises still lack the full exploitation of AI practices to reach the optimisation phase.

Table 1 summarises the categories used in the mentioned studies by mapping their features using macro dimensions. The full table is proposed in the Annex, where the most important features of each dimension are reported. It emerges that these dimensions are respectively considered in the different analysed papers, and each MM uses an average of 3 to 5 dimensions to assess the AI and BD application. The strategic alignment and organisational aspects in AI and BD management is a relevant feature while governance seems to lag behind and cultural and managerial approaches to AI and BD application need to be further investigated. In addition, the role of data and technology is fundamental in maturity identification and most of the works were considering these dimensions at an aggregated level. In fact, most MM frameworks consider various aspects of data maturity when dealing with production research but without considering the application of AI and BD to different types of operations. This is a gap that limits the capability of the MM to assess the AI and BD application specifically for the operations a company has to implement.

Upon the dimensions to be included in an MM, it is important to select and define the degrees of maturity. Derived from the literature above, between 4 and

Table 1. Comparison of the maturity dimensions considered in the different MMs.

References	Dimensions						
	Strategy	People	Organisation	Governance	Data	Technology	Operation
Comuzzi and Patel 2016	✓		✓	✓	✓	✓	
Schumacher, Erol, and Sihn 2016	✓	✓		✓		✓	✓
Pringle and Zoller 2018	✓		✓		✓	✓	✓
Arunachalam, Kumar, and Kawalek 2018					✓		
Bibby and Dehe 2018	✓	✓				✓	
Alsheibani, Cheung, and Messom 2019		✓	✓		✓		
Gentsch 2019	✓	✓	✓	✓	✓		
Hausladen and Schosser 2020	✓		✓		✓	✓	
Sadiq et al. 2021		✓	✓	✓	✓	✓	
Yablonsky 2021	✓	✓			✓	✓	✓
Wagire et al. 2021	✓	✓				✓	✓
Colangelo et al. 2022	✓		✓		✓	✓	
Hortovanyi et al. 2023	✓		✓			✓	✓

Table 2. Comparison of the levels of maturity in the MMs considered in the literature review.

References	Levels					
	1	2	3	4	5	6
Comuzzi and Patel 2016	Level 1	Level 2	Level 3	Level 4	Level 5	
Pringle and Zoller (Ovum), 2018	AI Novice	AI ready	AI proficient	AI advanced		
Arunachalam, Kumar, and Kawalek 2018	Incognizant stage	Initiation stage	Adoption stage	Routinisation stage		
Bibby and Dehe 2018	Minimal	Development	Defined	Excellence		
Alsheibani, Cheung, and Messom 2019	Initial	Assessing	Determined	Managed	Optimise	
Gentsch 2019	Non algorithmic enterprise	Semi-automated enterprise	Automated enterprise	Super-intelligent enterprise		
Hausladen and Schosser 2020	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Element AI 2020	Exploring	Experimenting	Formalising	Optimising	Transforming	
Yablonsky 2021	Human Led/Initial Analytics	Human Led, Machine Supported/ Advanced Analytics	Machine Controlled/ Advanced Analytics	Machine Led, Human Governed	Machine (Machine Led and Machine Governed)	
Wagire et al. 2021	Outsider	Digital Novice	Experienced	Expert		
Colangelo et al. 2022	Initialisation	Definition	Preparation	Implementation	Optimisation	
Hortovanyi et al. 2023	Novice	Beginner	Competent	Expert		

6 levels of maturity (Table 2) of AI and BD applications are identified and named, ranging from a minimum level (e.g. exploring, AI novice, initial, level 0) to a maximum level (e.g. transforming, optimise, super intelligent, level 5).

In general, the definition of an MM requires a design phase that strikes an appropriate balance between the complex reality and the need for model simplicity. A common design principle is to represent maturity as a number of cumulative levels where higher levels build on the requirements of lower ones. As can be seen in Table 2, the number of levels may vary from model to model, but it is important that the levels are well-defined and the existence of a logical progression through them is explained to the user. Identification of dimensions is critical for complex domains as this enables a deeper understanding of maturity, and the definition of the appropriate number of levels allows identifying specific improvement strategies. Mutually exclusive and collectively exhaustive dimensions and levels are essential (Becker, Knackstedt, and Pöppelbuß 2009). To conclude, the dimensions and the levels collected from this analysis (respectively in Tables 1 and 2) are used as input for the focus group and brainstorming activities with experts consulted in an iterative way to collect their opinions on the structure of the MM itself.

Methodology for developing a maturity model for AI and BD assessment

Grounding on the analysed literature related to previous MMs and the application of AI and BD in the process industry, an interactive methodology has been structured to develop the MM. Given the plethora of approaches existing in literature, the involvement of a group of experts facilitated the choice of dimensions and sub-dimensions as well as the levels of maturity. Moreover, being experts from the process industry, they helped

Table 3. Experts involved in the workshops classified according the criteria.

Expert #	Country	Type of organisation	Expertise in AI/BD	Years of experience
1	Netherlands	Consultancy	Strategic consultancy to process industry companies	25
2	Spain	IT provider	AI and BD for process control and maintenance	20
3	Spain	Consultancy	Supply chain, change management, business models	10
4	Italy	Industry	Supply chain, digital transformation in process industry, roadmapping	20
5	Italy	Research organisation	Optimisation and simulation, digital transformation in manufacturing and process industry	5
6	Germany	Research organisation	Digital transformation in supply chains of the manufacturing and process industry, strategic roadmapping for the industry	15
7	Germany	Industry	Digital design, AI and Blockchain solution development and integration	5

to focus specifically on the needs and to target the feature of the MM to this sector.

For these reasons, a group of 7 highly qualified experts in the process industry and AI/BD have been created (Table 3). The experts were chosen according to the following criteria:

- Representing different European countries;
- Representing different typologies of organisations (Research organisations, consultancy, IT provider and industry);
- Experience in AI and BD applied to process industry in topics emerging from literature like strategy, operations management, workers, data and technology.
- Years of experience (from 5 to 25 years with a position related to process industry).

The group was limited to 7 people to facilitate discussion and interactions based on the material that had been prepared for them.

The experts have been involved with 3 online workshops structured as interactive sessions during which, after a first preliminary presentation of the status quo, there was a long session of interaction and collection of feedback from the experts to answer to RQ1 and define how to structure a framework of MM for the process industry. In particular, the work was organised alternating the preparatory work of the research team and the interaction with experts as follows:

- Input for workshop 1: detailed Table 1 with the dimensions, and short description and the sub-dimensions (as in Annex 1);

- Workshop 1: presentation of the experts, the aim of the MM, and the findings from the literature. Initial discussion on dimensions for MM; clusterisation of dimensions, and choice of related sub-dimensions;

- Input for workshop 2: summary of the results of the workshop 1 and preparation of the updated list of dimensions; Table 2 and short description of each level.

- Workshop 2: presentation of the list of dimensions and sub-dimensions and validation. Discussion of the maturity levels as from Table 2; identification of the operations along which to assess the AI and BD application in the process industry;

- Input for workshop 3: summary of the results of workshop 2, preparation of the questions based on the list of dimensions, the maturity level and the list of operations;

- Workshop 3: share the complete list of dimensions and sub-dimensions before the workshop with the experts for final validation. During the 3rd workshop, the experts helped to triangulate the results from previous iterations and to formalise the structure of the survey taking into consideration the operations where to verify the application of AI and BD and the related levels of maturity.

Each workshop lasted from 1,5 to 2 h, and experts were asked to work offline on the dimensions with approximate time of 2 h. The overall process has taken 2 months. These steps helped to refine and choose the sub-dimensions and to confirm the maturity levels, to arrive at the overall framework of the MM and the structure of the survey. The discussion during the 3 workshops was supported by the lists of categories of AI and BD solutions identified in previous work by the team of research (Fornasiero et al. 2021) and reported in Table 4. A short description is available in the Annex and was provided to the experts.

Table 4. Taxonomy for AI and BD solutions.

AI solutions	BD solutions
Data understanding and characterisation	Data visualisation
Natural language processing	Data processing
Object and spatial recognition	Data protection
Machine learning	Data management
Intelligent planning	Computing and storage infrastructure
Expert systems	
Case based reasoning	
Intelligent agents	
Cyber-physical systems	

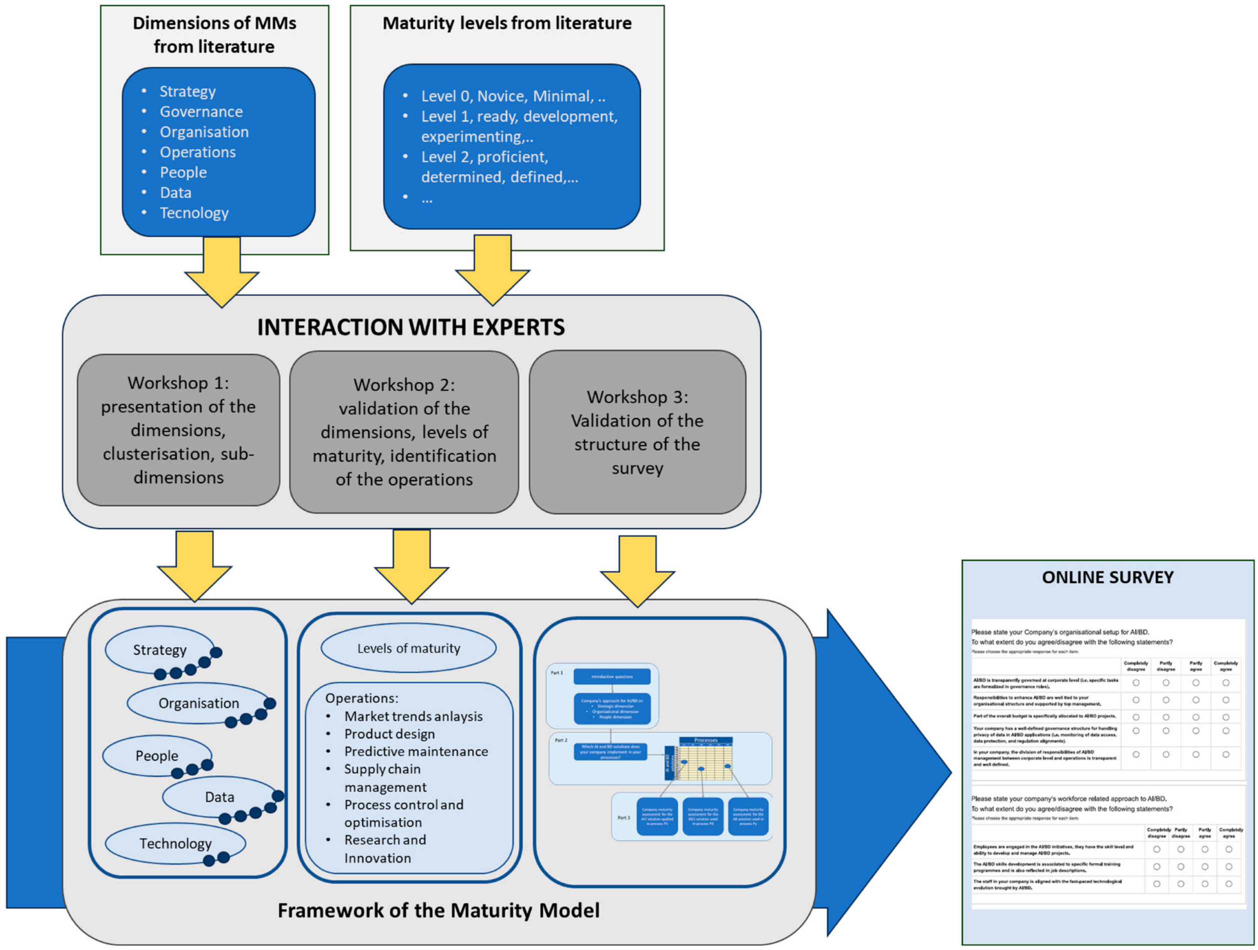

Figure 1. Methodology to reach the framework of the MM.

The overall methodology from models available in literature supports the definition of the framework of the MM for AI and BD in the process industry is represented in Figure 1. Starting from the dimensions of MMs proposed in literature and the maturity levels, three workshops have been organised to brainstorm and collect their feedback that has been integrated into the framework definition.

Thematic analysis was used to organise the material collected from experts. Thematic analysis is a qualitative research method for identifying, analysing, organising and describing themes found in collected data (Braun et al. 2019). This methodology is also useful for handling and clustering key features from existing information to produce a clear and organised output (Nowell et al. 2017). This method aims to search for relevant themes to describe a given phenomenon (Fereday and Muir-Cochrane 2006).

Specifically, during interaction with experts, it was used to start from the content of Table 1 (Annex 2) and discover similarities between dimensions and then sub-dimensions to cluster them according to the objectives of our MM (i.e. to assess the maturity of process industry in AI and BD application). The thematic analysis facilitated the clusterisation of the sub-dimensions from literature to obtain the sub-dimensions for the MM under development (adapted from Nowell et al. 2017 and Braun et al. 2019).

The framework of the maturity model for AI and BD assessment

Table 1 shows that the MMs in literature have no more than five dimensions of assessment to allow to cover different aspects without making the model too complex. Based on the results of the workshop 1, it was decided to group the dimensions identified in Table 1 and structure the MM according to the following five dimensions:

- **Strategy:** This dimension combines two dimensions from literature (strategy and governance) and includes the strategic alignment of the AI and BD applications with the company vision. This dimension is used to assess if a company has a clear strategy for AI and BD and enables corporate integration with top management's commitment. It enables to assess if AI and BD are considered as a competitive advantage for the company providing added value and being aligned with ethical, legal, and social implications (ELSI).

- **Organisation:** This dimension includes two dimensions from previous models (organisation and operations) and is used to assess capabilities of a company to define roles for AI and BD experts within the company and its organisational structure. These aspects can affect the financial status and companies' capabilities to handle their AI and BD applications internally. Winning companies have AI and BD responsibility assigned, utilise the expertise of data scientists as a formal organisational role, and benefit from full management support.
- **People:** This dimension aims to assess the role of employees towards digitalisation. People inside a company need to be trained to create awareness about AI and BD objectives of the company. AI and BD experts should have a fruitful collaboration with the other employees so that they are aware of the initiatives affecting their roles.
- **Technology:** This dimension concerns assessing the AI and BD solutions within the different operations of a company. It is, therefore, crucial to evaluate the maturity of each solution in terms of the integration of the solutions and the interaction with workers.
- **Data:** This dimension concerns the amount and structure of data to get AI and BD solutions by assessing velocity data capture, data access, transparency and quality of data, data mining and analysis.

The dimensions have been organised into sub-dimensions, representing principal factors to take into consideration when dealing with the organisation of AI and BD implementation in industrial companies, as reported in Table 5. The way the sub-dimensions have been defined from clustering literature is represented in Annex 3.

Workshop 2 was useful to refine and validate the results of workshop 1 and then the main activity was related to the definition of the maturity levels of the MM, where the experts decided to structure 4 levels. This can be considered as an intermediate solution between min and max number of levels proposed by other models. From Table 2 it is clear that each model has a different definition of the levels (i.e. simply numbers or descriptive). In particular, the levels for this MM are characterised as follows:

- **Level 1** – little or no adoption of the AI and BD solutions: companies have little knowledge of the topic, and the technology is not applied in practice in the companies.
- **Level 2** – experimenting AI and BD solutions with limited use: companies are starting to experiment and test some solutions along their processes.
- **Level 3** – on the way of formalising and adopting AI and BD solutions: companies are at a good stage of implementation of some solutions with high impact on the processes.
- **Level 4** – full adoption and optimisation of AI and BD solutions: companies that are champions of some solutions technology that is well established and its importance for their processes is recognised.

During workshop 2, it emerged the importance of assessing the implementation of AI and BD at the operational level, to go deep in the understanding of the role of these applications in supporting different types of activities. As for the classification of the operations, a preliminary list was proposed to experts based on previous works mapping AI and BD solutions (Govender et al. 2019; Toorajipour et al. 2021; Fornasiero et al. 2021). The experts agreed to classify 6 categories of operations:

- **Market trend analysis**: companies can use AI and BD for market and business trends analysis to adapt products/services to future demand and customer needs by obtaining strategic information and data from internal and external sources. Open innovation taps into knowledge and assets available within and beyond a single company, along with any relevant data. It includes the following activities: Sales, Customer Relationship Management, Consumer Behaviour Analysis, Market Scenario Analysis, Demand Management and Forecasting.
- **Product design**: activities of conceptualising, creating, and evolving products' features to solve customers'/users' problems or address specific needs in a given market through AI and BD supporting simulation, designing, cost assessment, and feasibility study. Product customisation is included, too, since it is closely related to design in alignment with particular customers' desires, increasing customer perceived value of a product with product configurators, and product matching systems.
- **Predictive maintenance**: AI and BD are applied to detect possible failures and defects of machinery in the early stages, prevent major failures and predict future stoppages. The objective is to maintain the level of product and process quality and service, which requires the capture of a lot of data from sensors applied to machines and information from periodic reports and planned maintenance.

Table 5. Full list of dimensions and related sub-dimensions in the proposed MM.

	Sub-Dimension	Description
Strategy	Importance of AI / BD decisions in the company's strategy	Company's strategic alignment with AI and BD applications, i.e. alignment of AI and BD with other business goals and degree of the relation of data to the business goals.
	Interest in the company's culture	Cultural attitude in the company towards AI and BD, i.e. interest in AI and BD initiatives, data-driven culture, and the approach for change management.
	Value adding potential of AI/BD	Contribution of AI and BD applications to create added value in a company, i.e. competitive advantage by AI and BD applications for the company and stakeholders.
	Consideration of ELSI	Definition of an explicit strategy for taking care of ELSI when implementing AI and BD, including the institution of an ethics manager.
	Awareness and monitoring strategies for the ELSI	Degree of awareness and monitoring strategies for the ELSI (Ethical, Legal, Social Implications) and their alignment to the company's strategy.
Organisation	Transparent Governance	AI and BD governance in a company, i.e. transparency and incorporation of governance roles (like Chief Digital Officer and Chief Technical Officer-CDO/CTO) at the corporate level and their association to company KPIs.
	Responsibilities in the organisational structure	AI and BD responsibilities tied to the organisational structure of a company, i.e. AI and BD responsibilities centralisation, existence of roles like data scientists, data managers, and AI experts.
	Budget allocation to AI/BD	Availability of financial and economical budget specifically for AI and BD development and monitoring, i.e. dedication of financial resources to AI and BD projects, economic evaluations, and the level of funding for the AI and BD -related sectors.
	Handling of data privacy	Privacy management strategy, with respect to the governance of data access, privacy protection, and regulation alignments.
People	Engagement of employees	Engagement of employees within the AI and BD initiatives, i.e. their skills level and ability to develop AI and BD projects and solve relevant problems, and top management support.
	Skill development	AI and BD skill development associated with the corporate and functional levels.
	Alignment to technological evolution	AI and BD skill level in the company, i.e. staff awareness and alignment with the fast-paced technological evolution.
Technology	Integration in processes and applications	Level of usage and integration of AI and/ BD within the different steps of each process, i.e. the capability of AI and BD technologies to support activities along processes like product design, sourcing, innovation, production and maintenance.
	Balance between technology and human intervention	Degree of decision-support by AI and/ BD at the process level, i.e. the capability of the system to support workers and to keep them in the loop, leaving a degree of decision to them.
Data	Data access	Richness of available data concerning internal and external data.
	Transparency of data	Transparency on available data of internal and external data.
	Updating of internal and external data	Frequency of data updates related to real-time data gathering.
	Quality of data	Data quality measured as the completeness of data collected in terms of frequency, missing data, formatting, and unique identification of the source.
	Processing of data	Capabilities to process unstructured data by AI/BD.

- **Supply chain management**: AI and BD are applied to support planning, executing, and controlling the operations of the supply network with the purpose of effectively meeting customer needs. Complex requirements, deadlines, and restrictions often conflict/overlap; hence, data models and intelligent planning can help find optimum configurations that balance different prioritised requirements and commitments. It includes activities like: Procurement, Production, Storage, Distribution, Network Design, Logistics Systems, Supplier Relationship Management, Contract Management, Sourcing, and Scheduling.
- **Process control and optimisation**: AI and BD can help adjust processes to maintain or optimise a specified set of parameters without violating process constraints. Internet of Things (IoT), cyber-physical systems and digital twins are based on AI and BD for modelling and simulating complex processes, thus avoiding expensive trial and error calibration, for example. It includes activities like: Process and Equipment Monitoring, Quality control and monitoring, and Process Redesign.
- **Research and Innovation**: companies need to manage effective allocation of resources (human, physical, financial) for the introduction of new products/services or the improvement of existing ones. Many AI and BD-related solutions play a role here, e.g. data management, intelligent planning, data visualisation, cyber-physical systems, data understanding and characterisation, natural language processing, etc. It includes activities like: Scenario Based Analysis, Optimisation/Simulation, HR Management, Risk Management, Collaborative/Joint Innovation Platform Development, Process Redesign, Development, Testing, and Piloting.

In workshop 3, after the validation of the results of the previous workshop, the experts contributed to the development of the structure of the survey. Given the complexity of assessing the AI and BD application from strategy to operations, it was agreed to have an innovative approach and to split the assessment into three parts: (1) questions at the company level; (2) selection of AI and BD solutions used in the company and relative operations where they are used; and (3) questions at the operational level. Beside strategic, organisational and workforce dimensions where it is necessary to make an aggregated assessment, it was decided to consider the specific application of AI and BD in different operations categories.

Therein, as shown in Figure 2, the first part of the MM aims at assessing the overall approach of the company to AI and BD implementation, considering the first 3 dimensions mentioned in Table 4: *Strategy*, *Organisation* and *People*. The second part of MM is used to map the AI and BD solutions as they are implemented specifically in the operations (i.e. market analysis, supply chain management, production control, predictive maintenance and research and development) and to assess the dimensions of *Technology* and *Data,* addressing the specific application of the AI and BD to operations. The user is asked to identify the most used AI and BD solutions in her/his company and to identify in which operations they are used. Then she/he is asked to answer questions specifically for each of these matching (AI and BD solutions versus operational processes). The answers to these questions are interpolated to obtain the overall score for these 2 dimensions (*Technology* and *Data)*.

The MM is conceived to be used by the single company to assess its level along the 5 dimensions and, most importantly, to benchmark with the other companies of the same sector or the process industry as a whole. The results are shown per dimension, comparing the maturity of the benchmark, which can be either the full sample or the sub-sample of the specific sector. Several analyses are possible for the user, as described in the later sections. The scores given to each dimension are aggregated to calculate the overall score of the related dimension. This structure has been used to define an online survey to be submitted to companies and providers from the process industry.

Data collection

Following the development phase, a data collection phase was conducted to validate the MM and collect initial insights into the maturity of AI and BD solutions in the process industry. This validation through a survey approach verifies the accuracy and repeatability of the MM and its results (Gökalp and Martinez 2022). The questionnaire definition, data collection, and analysis

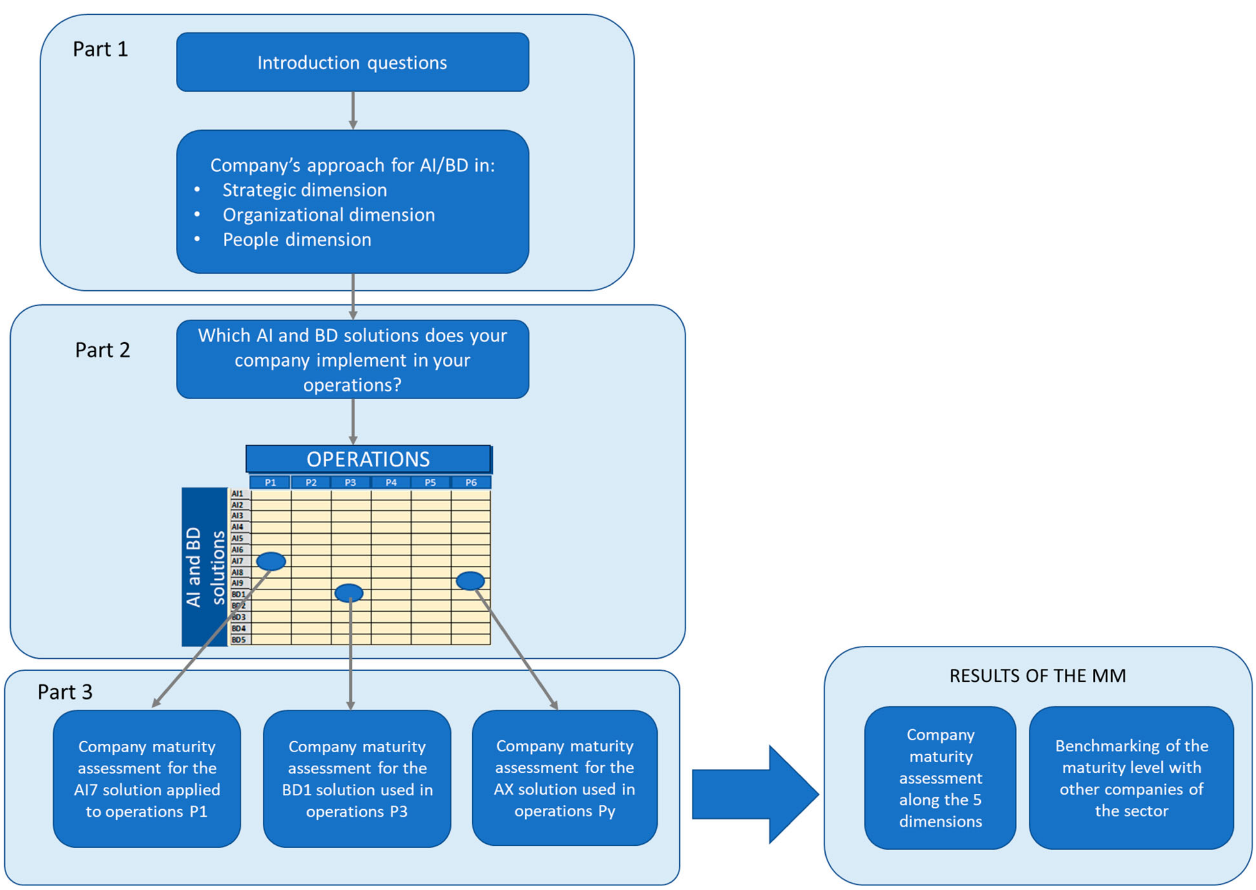

Figure 2. Framework of the developed MM.

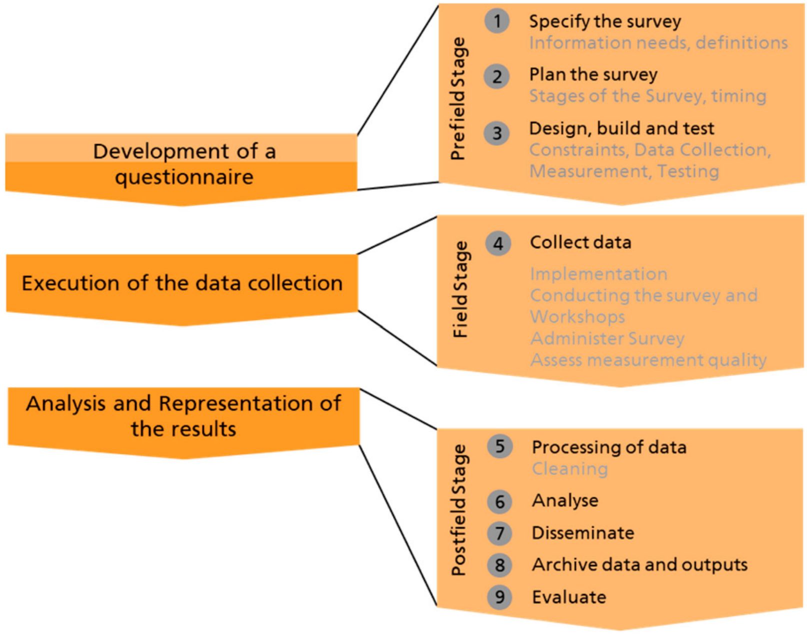

Figure 3. Detailed Data Collection Research Methodology (Forza (2002) and Queiroz and Telles (2018)).

phases followed the data collection research methodology described by Forza (2002) and adapted by Queiroz and Telles (2018), as illustrated in Figure 3. The data collection process is based on identified information needs (maturity assessments of current AI and BD solutions in the process industry) and constructs definitions (defined sub-dimensions in each dimension). Due to the limited number of open-ended questions and a large number of targeted experts in the European process industry, an online survey approach was used for data collection instead of other techniques, such as semi-structured interviews. Following the development and implementation of the questionnaire, it was promoted to the target group, and the answer rate was monitored continuously. The subsequent analysis and result representation steps involve processing and cleaning of the raw data, conducting analysis stages, disseminating the findings, and evaluating the overall process (Forza 2002; Queiroz and Telles 2018).

The online survey questionnaire for assessing the different dimensions of the MM closely follows the structure of the underlying maturity model. Each maturity sub-dimension is covered by one question measuring the related maturity level (Level 1 – Level 4) by assessing a level of agreement with a representing statement (Completely disagree – completely agree). Full agreement indicates a Level 4 maturity, while full disagreement indicates a Level 1 maturity. Figure 4 shows a sample part

Please state your Company's organisational setup for AI/BD.

To what extent do you agree/disagree with the following statements?

	Completely disagree	Partly disagree	Partly agree	Completely agree	No answer
AI/BD is transparently governed at corporate level (i.e. specific tasks are formalized in governance roles).	○	○	○	○	○
Responsibilities to enhance AI/BD are well tied to your organisational structure and supported by top management.	○	○	○	○	○
Part of the overall budget is specifically allocated to AI/BD projects.	○	○	○	○	○
Your company has a well-defined governance structure for handling privacy of data in AI/BD applications (i.e. monitoring of data access, data protection, and regulation alignments).	○	○	○	○	○
In your company, the division of responsibilities of AI/BD management between corporate level and operations is transparent and well defined.	○	○	○	○	○

Figure 4. Sample questionnaire extract for companies in the process industry for the dimension organisation.

of the questionnaire focusing on the maturity dimension *Organisation* and the questions relating to the five organisation-related maturity sub-dimensions.

The final questionnaire consists of 6 question groups (general questions and 5 maturity dimensions) comprising a total of 30 single questions. The general questions assess the participants' work experience, role, company (size, sector in the process industry), and the implemented AI or BD solutions (category of AI and BD, area of implementation, short description). These questions ensure industry focus, enable data cleaning, and facilitate further result analysis. Independent AI and BD experts with industry experience pilot-tested the questionnaire to assess its understandability and item clarity as a final step in the pre-field phase before implementing the survey management system (Forza 2002; Queiroz and Telles 2018).

In the first step of the data collection phase, the finalised and tested questionnaire was integrated into the 'Lime Survey' survey tool, and various paths through the survey were modelled. This questionnaire implementation was tested by the technology and industry experts who had a similar profile to the target group ensuring usability, understandability, and correctness. After this pilot study and minor modifications in the wording, providers and users of AI and BD solutions were contacted and directed to separate surveys via individual links to ensure appropriate question formulations for the target group.

Findings

The online survey for MM assessment in the process industry was conducted from July 2021 to May 2022 and complemented by 2 workshops among industry experts for cross-validation. Through targeted online communication via industry associations, newsletters, social media, and direct approaches, experts from the sectors under consideration were specifically addressed, resulting in over 100 participants. The result analysis focused on 30 participants with implementation cases, providing specific insights and lessons learned. The preliminary results focus on representative examples from Chemicals, Engineering, Steel and Water. The survey participants were from different EU countries, with a focus on Germany, Spain, Italy, Austria, and Greece. Of the participants, 43% represented companies with more than 500 employees, 7% represented companies with 251–500 employees, 37% were from companies with 50–250 employees and 13% were from companies with less than 50 employees mainly software providers.

Aggregated maturity in the process industry

The initial analysis involves an overview of the five dimensions by summarising the different sub-dimensions and generating averages for each dimension. Figure 5 presents a comparison of these averages for the entire process industry at the dimension level, allowing for initial conclusions. The combined bar for each maturity category represents the relative frequency of each maturity level for the relevant sub-dimension (left axis). In addition, the average maturity rating for each dimension is plotted in grey on the right axis.

Overall, the results from the sample indicate that implemented AI and BD solutions in the process industry have high levels of maturity in the dimensions of *Strategy* and *Technology*, as evidenced by a higher percentage of Level 4 and Level 3 assessments. In contrast, the dimension of *People* shows lower maturity levels, with a higher rate of Level 1 and Level 2 assessments. Further examination reveals that less mature sub-dimensions of *skill development* and *alignment with technological evolution* have a high impact on the lower maturity, while

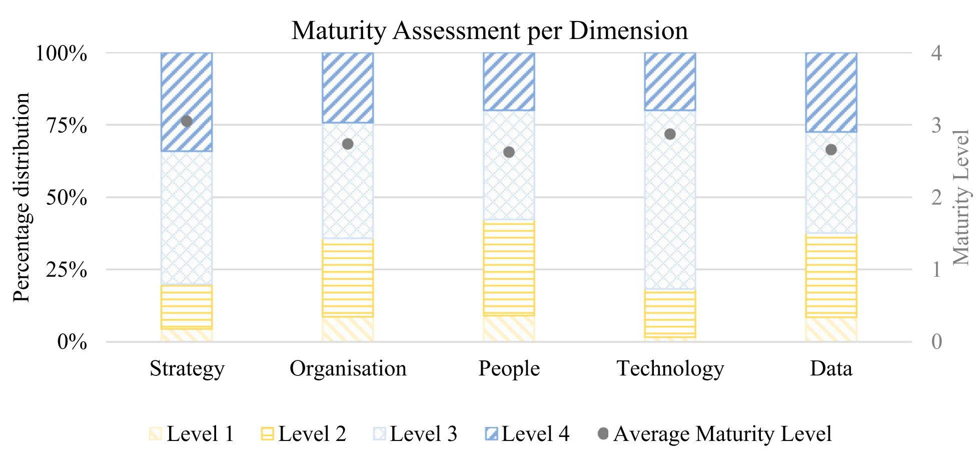

Figure 5. Percentage Distribution of maturity assessments per dimension and maturity level averages for the entire process industry.

employee motivation is rated as more mature. The two dimensions of *Organization* and *Data* exhibit comparable levels of maturity. Further analysis of the underlying sub-dimensions is required to explain these observations.

Overall, the survey indicates that the maturity of the implemented AI and BD solutions is considered relatively mature in the process industry. Only a small percentage of the surveyed implementation cases are assessed with lower maturity levels in different dimensions. The majority of implementations are rated at levels 3 and 4. From this aggregated view, drilldowns in the dimensions sectors, maturity sub-dimensions and technologies can be conducted to obtain more detailed results.

Detailed analysis of sub-dimensions

A detailed analysis of the sub-dimension within each maturity dimension provides more detailed insights into the different levels of maturity. This analysis helps to identify areas of action in future projects. By analysing the average maturity assessments per sub-dimension and excluding the distributions of different maturity level assessments, a clearer picture of aspects with higher and lower levels of maturity can be obtained, as shown in Table 6. Some areas, such as the value-adding potential of AI and BD solutions, data access possibilities, integration into the corporate culture and the consideration in the corporate strategy have already been implemented with a high level of maturity. On the other hand, areas with a comparably lower maturity are evident, particularly in the sub-dimensions of data processing, skill development, alignment to technological evolution, division of responsibilities and transparent governance. These results align with the challenges identified by Gökalp and Martinez (2022), which include insufficient internal skills, integration of new technologies and resistance to change.

To provide a comprehensive analysis, providers and users of AI solutions were separately questioned in the online survey. As an example, Figure 6 presents the perspectives on the maturity of different sub-dimensions within the dimension *Data*. The results show that the industrial users rated solutions implemented in their companies with a higher maturity than the solution providers, particularly in the sub-dimension of *Data access*. However, apart from data access, the response patterns are very comparable with lower maturity levels in *processing of data* and *updating data,* and higher maturity levels in *data quality* and *transparency*. Significant differences can also be observed in other dimensions, such as *integration in processes and applications* in the dimension of *Technology*, *engagement of employees* in the *People*, and *division of responsibilities* in the *Organization* dimension. Notably, industry users consistently reported higher maturity levels than solution providers in these areas, in addition to *data access*. These differences highlight

Table 6. Average maturity assessments for the different sub-dimensions.

	Maturity Dimension	Sub-Dimension	Average maturity
Company-related maturity dimensions	Strategy	Importance of AI / BD decisions in the company's strategy	3,18
		Interest in the company's culture	3,19
		Value adding potential of AI/BD	3,46
		Consideration of ELSI	2,71
		Awareness and monitoring strategies for the ELSI	2,68
	Organisation	Transparent Governance	2,58
		Responsibilities in the organisational structure	2,89
		Budget allocation to AI/BD	2,95
		Handling of data privacy	2,85
		Division of responsibilities	2,57
	People	Engagement of employees	2,74
		Skill development	2,55
		Alignment to technological evolution	2,56
Solution- related maturity dimensions	Technology	Integration in processes and applications	3,09
		Balance between technology and human intervention	3,06
	Data	Data access	3,30
		Transparency of data	2,98
		Updating of internal and external data	2,80
		Quality of data	2,89
		Processing of data	2,32

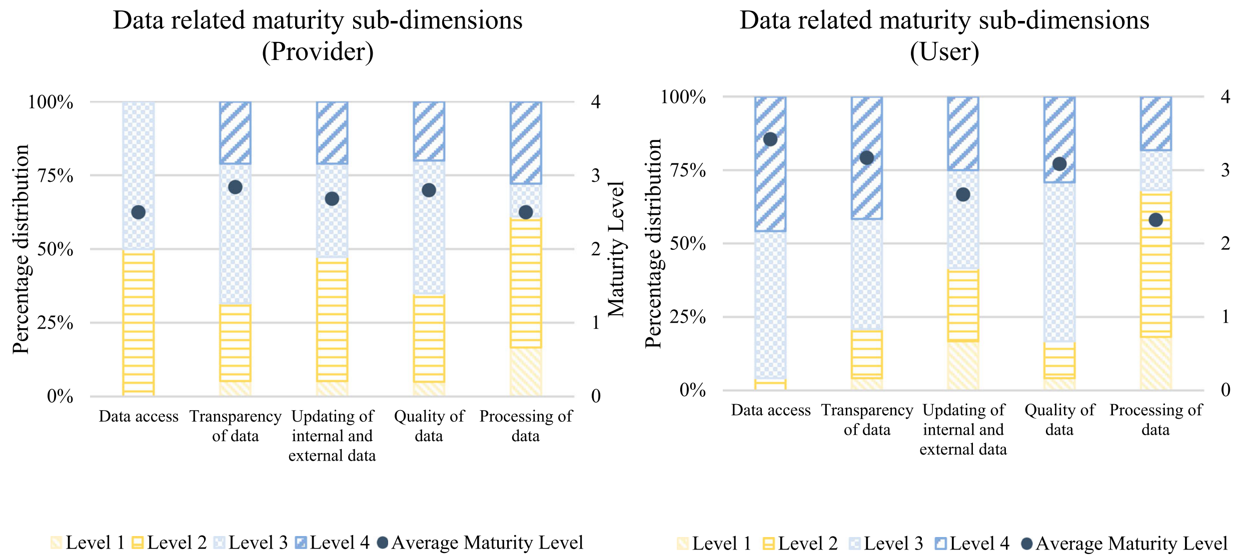

Figure 6. Sub-dimensions of the data dimension, provider vs. user.

the importance of considering the perspectives of both providers and users.

AI and BD solutions-specific analysis

By analysing the applied solutions separately, technology-specific maturity conclusions can be drawn. The exemplary evaluation of the four most frequently mentioned AI and BD solutions in the survey (Machine Learning, Expert Systems, Object and spatial recognition, and data processing) shows similarities as well as differences on the aggregated dimensions level (Figure 7). The analysis focuses on the dimensions related to the specific solution implementation (*Technology* and *Data*), as well as solution-independent dimensions (*Strategy*, *Organisation* and *People*) to identify interactions.

The detailed analysis of the sub-dimensions in the solution-related maturity dimensions *Technology* and *Data* reveals comparable maturity assessment curves for the different AI and BD solutions, as presented in Figure 8. The sub-dimensions *data access* and *data quality* consistently receive higher maturity ratings across the four analysed AI and BD solutions. However significant differences exist in other sub-dimensions. In the sample from the process industry, implementations with object and spatial recognition technologies are assessed with a higher maturity compared to expert systems or machine learning solutions. The analysis of the solution-related

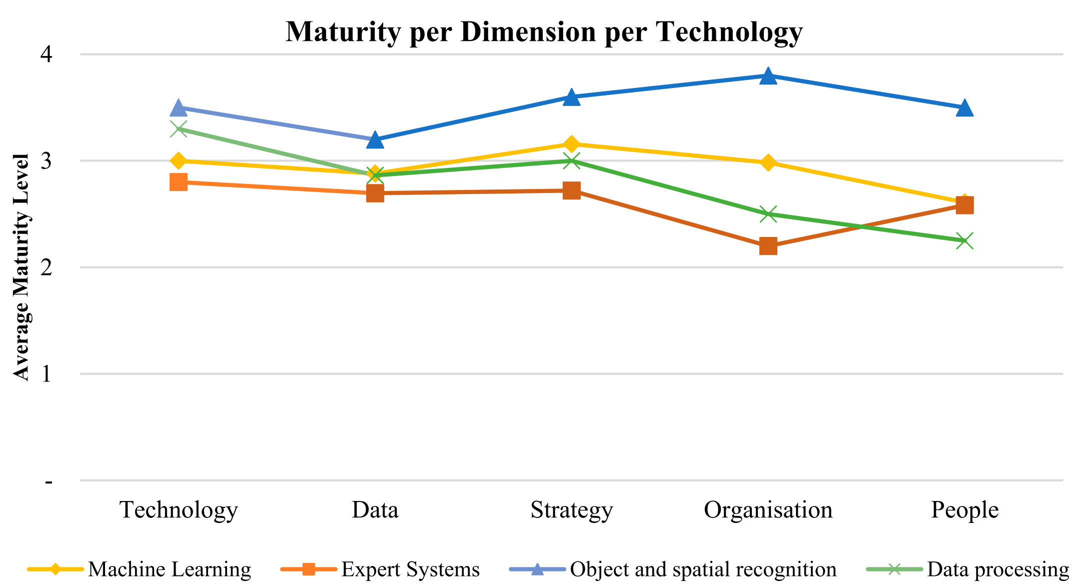

Figure 7. Maturity dimension per AI and BD applications.

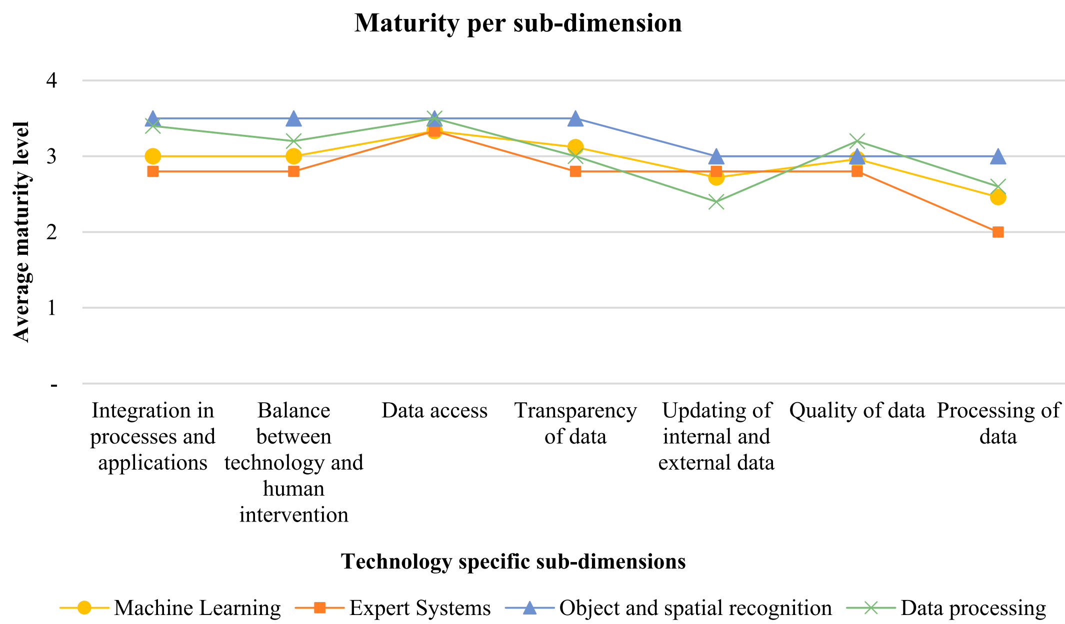

Figure 8. Sub-Dimension averages for the 4 technologies.

maturity dimensions of *Data* and *Technology* demonstrates that the different categories of AI and BD are assessed comparatively similarly. Higher ratings in one dimension are likely to correspond to those in other dimensions. This observation extends to the dimensions that are independent of the specific AI or BD solution.

Benchmarking

In addition to analysing the overall results for the process industry, each company can assess the maturity along a single technology or individual dimensions, and this is crucial for identifying areas of improvement and above-average maturity. By assessing the maturity for different sub-dimensions in the survey, a company-specific maturity score and distribution of the ratings can be obtained and used for benchmarking with other companies of the same sector or of the process industry in general. This direct benchmarking process allows practitioners to assess the progress made and identify current capability or organisational gaps for further improvement in AI and BD usage (Hortovanyi et al. 2023).

As an example, the assessment of a water sector company's Machine Learning solution can be benchmarked against other companies in the sample (Figure 9). The detailed analysis shows that the company's maturity is clearly above the sample average in the dimensions of *Organisation*, *People*, and *Technology*, but below-average in the dimension of *Data*. This information can be useful for the company as a preliminary analysis of where to improve and increase investments.

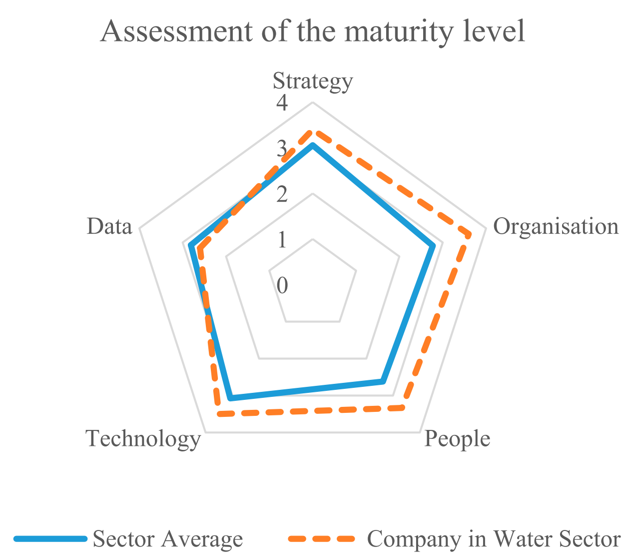

Figure 9. Dimension-based benchmarking.

Further benchmarking analysis at the sub-dimension level reveals that the aspects of *data quality* and the *updating of data* impact the overall maturity of the implementation, as depicted in Figure 10. Potential fields of action can be derived directly. In this example, a potential field of action includes further optimising the existing solution and achieving a higher overall maturity in the dimension of *Data*. Prioritisation of measures should focus on achieving comparable averages across all dimensions before improving areas already above-average. These results demonstrate the functionality of the MM, the questionnaire design, and its evaluability. They also highlight dimensions with high and low

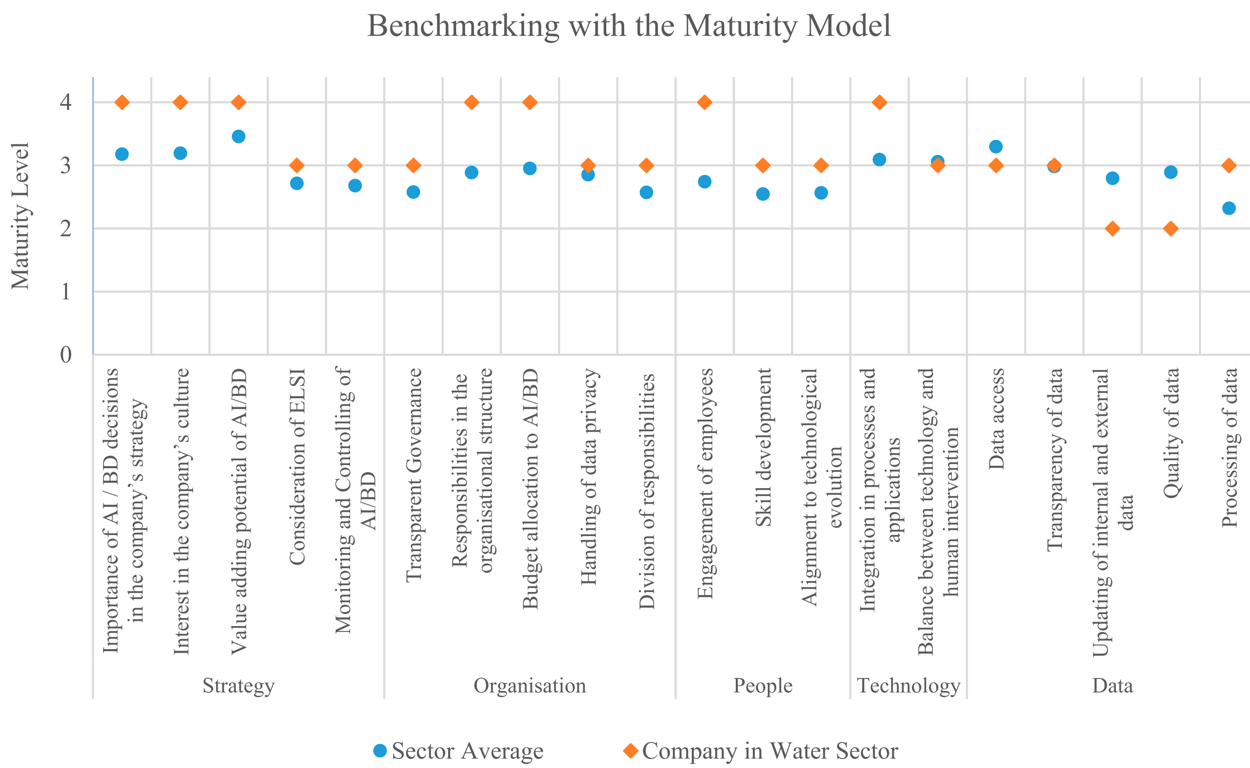

Figure 10. Sub-dimension for benchmarking of one company.

maturity levels within the process industry across different dimensions and sectors.

Discussion

Since digital transformation is a broad topic and related MMs have been developed in several areas, this study focused on AI and BD as two important technological advancements to help companies in the process industry with specific questions focusing on the challenges and opportunities arising from AI and BD implementation as two important enabling technologies of Industry 4.0. The developed MM differs from the literature so that it allows to collect both the company and industry perspectives through benchmarking. Furthermore, it differs regarding the focussed technologies and the industry-specific approach. The comparison with existing models in the literature reveals the basic characteristics of several models but does not give clear guidance for the design phase. In this work, the MM is designed with a build-and-evaluation iteration where experts support the definition of the MM with in-depth discussion. They have been involved step by step along the definition of dimensions, sub-dimensions, levels and questions to deploy in the online survey for validation and preliminary results.

AI MMs are differentiated by descriptive, prescriptive, and comparative characteristics (De Bruin et al. 2005; Sadiq et al. 2021). Descriptive models measure the current state of AI in a specific environment; prescriptive models provide recommendations for improvement, and comparative models benchmark an organisation's AI capabilities against an average. In this paper, we develop a new MM focusing on the descriptive and comparative approach by describing a detailed recording of the current maturity through the developed questionnaire and the comparison with sector averages. Prescriptive characteristics and conclusions derived from using the MM are investigated and described as part of the overall framework proposed by the EU research project AI Cube, where we offer guidelines and roadmaps for industrial usage in the process industry sectors based on the maturity assessment. Particularly, regarding the descriptive and comparative properties of the MM, great importance was associated with the practicability and appropriateness of the assessment during the development of the model. This was tested in the online survey to directly exclude a major point of criticism of existing models (Sadiq et al. 2021).

This MM has been conceived to help companies gain a competitive advantage from AI and BD solutions (Lichtenthaler 2020) based on assessing the level they are with strategic and organisational dimensions as well as with people (workers) acceptance of these technologies along their processes as part of the overall digital transformation efforts. As motivated by addressed literature gaps, this MM model helps companies to assess the process of AI and BD integration solutions in practice (Sadiq et al. 2021), considering quantitative measures for self-assessment and benchmarking (Chen et al. 2022). As emphasised by Hortovanyi et al. (2023) and Nayernia, Bahemia, and Papagiannidis (2022), these insights from the created framework of the MM can help managers to assess the current capability gaps and to understand the most important fields of actions on the path to mature AI-based processes as an important part of the overall digitalisation efforts.

From the analysis, it emerged that companies from the sample applying certain AI and BD solutions, such as object and spatial recognition, are already very mature in dimensions like *Strategy* and *Organisation*. Other companies can take inspiration from these results and use them as a benchmark for their specific case. Looking at the specific AI and BD solutions, while *Technology* and *Data* dimensions have the same level of maturity, there can be significant differences in the other 3 dimensions. Therefore, any change management practice should focus on the *Organisational* dimension, with which the highest difference in maturity level is associated. Analysing the results per company, it emerged that companies with a high level of maturity in the *Organisation* and *Strategy* dimensions, then it is easier to arrive at high levels of maturity also in the other dimensions of AI and BD solutions.

The responses on the *Data* dimension show that users perceive higher maturities in the data access, transparency, and quality. The reasons can be associated with users' opinions being limited to the sectors they are operating and being more subjective to the company they work for. However, since providers have a broader view of various sectors and implementation cases in the process industry, their weight on average maturity levels is the average of all sectors. Hence, their points of view help to balance benchmarking among sectors and facilitate the evaluation of the process industry as a whole for potential stakeholders. On the other hand, the assessment of the users helps each sector in the process industry to have a better understanding of their self-assessment of maturity.

From the results of the sample, we can argue that companies in the process industry still lag behind *People*, *Data*, and *Organisation* maturity, with 58%, 62%, and 64%, respectively. These findings confirm what was already found by Hortovanyi et al. (2023) in regard to the assessment of digital maturity in the field of general digital transformation: at the beginning of a digital transformation, the focus lies on the strategic benefits of new technologies (strategy dimension) and the mastering of the technology itself (dimensions of technology), while the change process of the company's culture and organisation takes more time. Hence, the starting point of a digital transformation should consider emerging technologies deriving from the integration of AI and IoT with industry 4.0 beyond the existing applications, such as decision-support systems (Radanliev et al. 2021). After this initial stage is mastered and the organisational and personnel-related dimensions are more developed, the real progression in the capabilities does occur.

Considering the sub-dimensions, companies need to be more proactive in terms of *skill development*, *alignment to technological evolution*, *data processing*, and *division of responsibilities*. On the other hand, *Strategy* (80%) and *Technology* (82%) are conceived as the most mature dimensions. This maturity shows that organisations' management is ready to change to new solutions and that relevant technologies are available.

Conclusions

This study contributes to the literature in the domain of maturity assessment frameworks to help companies assess their maturity for AI and BD applications, supporting operational processes. The MM framework comprises 5 dimensions and 30 maturity sub-dimensions clustered from previous studies with the support of experts through consultation and validation. An online assessment tool was designed to help companies from the process industry evaluate the level of maturity of their AI and BD solutions.

The questionnaire of the MM is helpful for companies in the process industry to self-assess their maturity levels at the company and sector scale and to benchmark with other sits related characteristics that can be referred to decide the company's.

In terms of theoretical implication, this study has conducted a detailed analysis of existing MMs to fill the research gap of a specific assessment tool and maturity level measurement for a sector like the process industry. Hence, the study adds value in providing an MM and a maturity assessment tool that gives results at strategic as well as operational levels on AI and BD implementation, taking into consideration also ethical issues related to workers' involvement. Building upon existing MMs described in literature, this work is based on several iterations with experts in the area, that helped to validate the theoretical approach to identify the proper dimensions and operations to assess.

In terms of practical implications, managers can use this tool to understand which areas to strengthen for the full adoption of AI and BD solutions in different types of operations. Companies need to accompany the full implementation of technologies with appropriate actions that workers at all levels are committed to. The proposed

MM framework enables companies to self-assess their maturity level iteratively and comparatively. Further, it helps companies decide the dimension necessary to focus out of five dimensions (strategy, organisation, people, technology, and data). The top management can utilise the results of the MM setting new targets and dedicating financial and workforce resources. Additionally, companies can use the results with partners to share the best practices and monitor the related development paths.

From a systemic point of view, based on the maturity results collected from a large group of companies, it is possible to draw a tailored roadmap to AI and BD implementation at the sector level as well as an innovation path that goes beyond the technology per se with support of industrial associations and software providers. Although this framework is designed and validated in the European process industry, it would also help other sectors and beyond Europe.

Proposition of future research

The MM developed in this work is grounded on literature and was developed with the support of experts' opinions. For a first validation, a preliminary set of companies participated in self-assessment to determine their maturity level. The level of subjectivity of the development process can be smoothen by implementing the MLA on a broader scale with a larger number of companies from the same sector or within different industrial sectors. The additional insights gained in this process can provide additional paths to refine the dimensions analysed and to refine the question formulations. Moreover, larger sample sizes will enable further explorative statistical analyses to identify correlations between sub dimensions and factors. Further development through the involvement of other experts with different specialisations can also enhance the model's validity and generality.

Data collection for the model validation was conducted through an online questionnaire due to the expected size of the target group. Supplementing this method with more detail-oriented direct interviews with individual industry experts could provide further insights in a second phase after the initial broad data collection described in this paper. These case studies on applied AI/BD solutions can help to identify the root causes of unsuccessful integration projects and future practices for success in further research work.

Referring not to the development and validation process but to the actual maturity model, further maturity sub-dimensions not addressed in the first MM version can be considered to enlarge the information collected to assess a company's maturity level in its entirety. In particular, sub-dimensions related to ethical and legal problems could be strengthened by conducting a deeper analysis of the features expected for AI and BD (such as explicability, trustability, and transparency). This analysis should align with evolving requirements from European regulations. Individuals focusing on certain dimensions and the application in broader tests can enable further optimisation of the model in the next development stages.

Additionally, considering the interrelation between ethical issues, social sustainability, worker safety and well-being, and the interaction of companies with society and consumers could be an important development path. Collecting and comparing different perspectives from managers, workers, and consumers can provide a comprehensive assessment of maturity.

Another important area to explore based on the initial maturity assessment is the maturity level of AI and BD technologies in enabling strategies for environmental sustainability, such as pollution prevention and energy efficiency. The link between the current maturity level of these technologies and the connected company performance is another important aspect that could be analysed by surveying additional information on performance data.

Data availability statement

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

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Disclosure statement

No potential conflict of interest was reported by the authors.

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