MATURITY MODELS FOR THE USE OF ARTIFICIAL INTELLIGENCE IN ENTERPRISES: A LITERATURE REVIEW

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Abstract: *Artificial intelligence is a promising technology for companies to leverage optimization potential and remain competitive. Nevertheless, studies show that only a few companies use this technology. Maturity models can contribute to self-assessment and help to implement this technology. In this paper, capability, readiness and maturity models are presented based on a literature review and a qualitative analysis. Overall, the results show that the models can serve as a tool to assess and improve AI readiness and maturity. However, in order to fully exploit their potential from a user perspective, it is essential to further develop these models specifically for AI domains, ensure transparency in their design, draw clear conceptual boundaries and incorporate user-friendly assessment mechanisms. Furthermore, recommendations for action are made on the basis of this information.*

Key words: *Artificial Intelligence, Maturity Model, Adoption, Literature Review*

1. INTRODUCTION

The impetus for this paper arises from the recognition that there have been several preliminary works and literature reviews on this subject. However, either these works did not adequately consider specific artifacts that are important to the topic AI maturity models, or the explanations regarding these artifacts were not sufficiently detailed. Consequently, there exists a gap in the literature regarding a comprehensive investigation of these artifacts within the context of the examined subject. Through a systematic approach and comprehensive analysis, we endeavor to offer valuable insights that enrich the scholarly discourse on this subject matter. The detailed explication of these artifacts will contribute to a more nuanced and well-founded understanding of their relevance and potential implications for maturity models.

This paper commences with an introduction and an elaborate presentation of the fundamentals of maturity models. Within this introduction, relevant theoretical concepts and methodological approaches are introduced to provide readers with a comprehensive context for the subject matter. In the second chapter, an overview of existing models follows, which were identified on the basis of a literature review, then reduced, structured and sorted. In the third chapter follows the evaluation of the maturity models and presentation of the results. The paper ends with the discussion and conclusion.

1.1 Fundamentals of maturity models

Many AI technologies and applications developed in recent decades have reached market maturity and are now being sold commercially in digital products and services (Schmid et al., 2021). Maturity models serve as a kind of tool that makes it possible to determine the positioning of one's own organization and to identify development prospects (Becker et al., 2009a). Although various types of maturity models exist, they share common characteristics. They include a set of indicators or process areas in multiple maturity levels, with a description of the required performance of the indicators at these levels (Fraser et al. 2002).

According to (Mettler, 2010), the implementation of the components into a maturity model is done in various ways in practice. In the literature, a basic distinction can be made between two types of maturity models. (Mettler, 2010) distinguishes in his work between optimization models and evaluation models:

1. Optimization models try to specify an idealized development path in order to achieve an improvement for the object under consideration (Paulk et al. 1993).
2. Evaluation models also aim at the continuous improvement of the object of observation, but the focus is rather on the aspect of comparison. Often, no explicit development path is specified, but it is rather implicitly contained in the models (Winter et al. 2016).

Another distinction often made in the literature is according to the typology of maturity models, which manifests itself in the design of the maturity model. Maturity models can be divided into three basic types (Fraser et al., 2002):

1. Maturity Grids (maturity grids, maturity tables): Grid models use a grid structure in which each activity in each maturity level is represented by textual descriptions. As a result, these models have lower complexity and usually consist of only a few pages of text.
2. Capability Maturity Model-like models (CMM): models based on the CMM approach have a more structured but also more complex form, where each stage is described by a specific sequence of measures and activities addressed to specific goals. Although there are general descriptions of maturity for each level, there are no individual descriptions for each activity at each maturity level.
3. Likert-like questionnaires: The Likert-like questionnaire, when constructed in an appropriate manner, can be considered a simple form of a maturity model. In this type of model, the "question" simply represents a statement of "good practice" by the object of assessment and rates the relative performance of the organization on a scale from 1 to n. It should be noted that this type of questionnaire becomes a checklist when n=2.

The aforementioned characteristics of maturity models primarily pertain to their formal content. While the fundamental objectives and structure of the models have been elucidated, the further assessment of these models necessitates a more profound examination of their characteristics. Particularly, evaluating maturity model attributes requires a deeper analysis (Jording, 2018). The classification of these characteristics are based on the work of (Jording, 2018), (Mettler, 2010) and (Ahlemann et al. 2005). (Mettler, 2010) distinguishes the characteristics of maturity models into general characteristics, construct-specific characteristics, and model-specific characteristics. Jording (2018) differentiates the characteristics into general attributes, attributes related to conceptualization, attributes related to operationalization, retention attributes, and framework attributes. The following sections are based on these characteristics of maturity models and present a compilation of relevant attributes for the evaluation.

1.1.1 General Attributes

The novelty value refers to the extent to which the model draws upon existing solutions, meaning it either addresses an existing problem in an alternative way (variant or version) or provides a completely new problem-solving approach (innovation) (Mettler, 2010).

The institutional background in addition to individual authorship describes, if there is an overarching institutional affiliation or connection (Jording, 2018). A distinction is made between four attributes. The model was developed by researchers affiliated with universities or institutional research establishments. The model was created by one or more individuals who are not associated with scientific institutions or the organizations mentioned here and work independently. The model was created by one or more individuals who are not associated with scientific institutions or the organizations mentioned here and work independently. The model was developed by a company or directly commissioned by a company. In many cases, these may be consulting firms. Since models from consulting firms were not considered in the literature review, so this characteristic indicates that the examined model is based on previous work by a consulting company. As the last and fourth attribute, when model was devised by an association, society, or similar organization. The model was developed by a government institution or directly commissioned by such an organization (Becker, 2009b).

The model's breadth defines the scope within it was designed and determines whether it is a sector-specific or none-sector-specific-model. The target group specifies the perspective from which the maturity model is viewed, either from a management-oriented or technology-oriented standpoint (Mettler, 2010).

Regarding accessibility, three distinct variants are distinguished: freely accessible, cost-based, and consulting services (Jording, 2018). In the course of the research, the access was free of charge, whereas external individuals have to bear costs. For this reason, the accessibility of a model, even if associated with only a minor expense, was classified as fee-based.

Within the context of priorisation, the examination of the models assesses whether they conduct an evaluation of their contents. It takes into account that not all content underlying the evaluation contributes equally to the performance of the evaluated object (Jording, 2018). Additionally, the model is evaluated regarding its adaptability to individual users, where specific questions or evaluations can be excluded or modified (Ahlemann, 2005; Jording, 2018). In terms of the geographical scope, the assessment determines whether the maturity model considers a geographical reference during its validation or application (Jording, 2018).

Table 1: General Attributes

Characteristics		**Parameter Value**				
General Attributes	Institutional Background	Science	Individual	Company	Association or Society	Government Organization
	Novelty Value	Innovation		Variant		Version
	Accessibility	Freely Accessible		Cost-based		Consulting Services
	Priorisation	Priorisation possible		Priorisation Proposal		Adaptability
	Target Group	Management-oriented		Technology-oriented		
	Geographical Scope	Yes		No		
	Breadth	Industry-agnostic		Industry-specific		

Source: Adapted from (Jording, 2018; Mettler, 2010)

1.1.2 Model-Specific Attributes

In regard to the conception of the model, the purpose of use and the Definition of maturity levels were taken into account. The purpose of use defines whether the model was primarily developed for optimization or evaluation purposes (Mettler, 2010). The definition of maturity levels can be approached either through a Top-Down or Bottom-Up approach (De Bruin et al., 2005). The determination of the approach for deriving maturity levels is specified in the maturity level definition (Mettler, 2010). Unless explicitly stated, as in the work of (Alsheiabni et al. 2019), that a Bottom-Up approach was used, it will be assumed that Models aligning with the design frameworks of (de Bruin et al., 2005) or (Becker, 2009a) are based on a Top-Down approach, as they implicitly follow a Top-Down approach (Mettler, 2010).

Regarding the application of the maturity model, further differentiation is made based on the data collection method. The data used to assess the maturity can be gathered through either self-assessment or external assessment. Depending on the maturity level of the subject under consideration and the complexity of the maturity model, professional assistance may be required. An essential component of the data collection method is the data collection technique, which determines the specific means through which the data is gathered. This could include methods such as interviews, surveys, observations, or document analyses. The chosen data collection technique significantly influences the format and structure of the collected data. Finally, the tools provided to facilitate data collection are specified. These tools could include handbooks, checklists, or software tools that support the data collection process (Mettler, 2010).

Table 2: Model-Specific Attributes

Characteristics		**Parameter Value**			
Model-Specific Attributes	Data Collection Technique	Interview	Survey	Observation	Document Analysis
	Assessment	Self-Assessment	Supported by Third Parties		Assessment by Third Parties
	Tools	None	Document-based		Computer-assisted
	Maturity Level Definition	Bottom-Up		Top-Down	
	Purpose of Use	Optimization		Evaluation	

Source: Adapted from (Jording, 2018; Mettler, 2010)

1.1.3 General condition

The examined maturity models differ in terms of their empirical foundation. According to (Ahlemann et al. 2005), this characteristic can be interpreted as a quality indicator of a maturity model and is defined and differentiated as follows:

1. Models have no or no documented foundation.

2. Models are explained and motivated based on case studies, making the results understandable based on individual cases.

3. Models have an empirical foundation based on a broad empirical analysis involving a large number of experts in the construction of the model.

Regarding the third point, it can be added that in the study of (Jaaksi, 2018), which was conducted through 11 expert interviews, it is stated that the results are not generalizable due to the low number of interviews. In this Paper, a supporting number of more than 20 expert interviews is assumed as a basis for an empirical foundation**.**

Table 3: General Condition

Characteristics		Parameter Value		
General Condition	Empirical Foundation	No/Not documented	Case Studies	Empirical Foundation

Source: Adapted from (Jording, 2018; Mettler, 2010)

1.2 Objective of the paper and Research Questions

The objective of the paper is the identification and application areas for maturity models. The research questions (RQ) are as follows:

RQ 1: Which maturity models exist in the literature and how do they differ?

RQ 2: What are the application areas of these maturity models?

RQ 3: What various terminologies are used in relation to indicators within models and the model itself, and how can be categorized?

2. RESEARCH METHODS AND LITERATURE OVERVIEW

The research questions are answered with a literature search and subsequent qualitative evaluation. For this purpose, a general overview of the topic was first made and the research questions were refined before starting the actual search. For the research process, the works of (Snyder 2019; Webster & Watson 2002) were consulted and guided by their research process. The systematic process of (Wright et al., 2007) was also used in the literature search. The authors divided the steps of the systematic review into: (1) research question, (2) research protocol, (3) literature search, (4) data extraction, (5) quality assessment, (6) data analysis and results, and (7) interpretation of results.

After establishing the research questions, a continuation protocol was established to help systematically identify papers in the literature review. The procedure in a research protocol can be described as an iterative process with four steps: (1) search, (2) screening, (3) data extraction, and (4) data analysis. For step 1, the database was selected and keyword chains were created. Scopus (www.scopus.com) was used as the database because many economics papers are indexed there. The next step was to select the keywords for the research topic. Key terms were varied according to both synonyms and abbreviations. The search period for the articles was from December 2022 till March 2023. After the relevant papers were selected, data extraction and analysis took place. The relevant papers are presented in the following.

The universal maturity model by (Burgess, 2018) has six maturity levels. This is intended to enable assessment of the entire organization, but can also be applied to individual areas of the company. Burgess takes a solution-oriented approach in which AI applications are assigned to the desired solution area in a matrix. The assessment of maturity levels is subjective and is done through interviews. After developing the AI maturity matrix, Burgess' next step is to create a heat map. The heat map provides a top-down perspective on areas where AI solutions are desirable, economically viable, and/or technically feasible and is intended to identify the types of AI applications that could be applied in each area to achieve the desired goals. Using the combination of the maturity matrix and the heat map, business areas can be assessed against 4 main factors and their sub-indicators. How these are to be assessed is not apparent.

(Jaaksi, 2018) identified five indicators that influence the maturity level in an organization in his study by means of 11 expert interviews, but points out that the maturity model cannot be generalized due to the small number of interviews. The development of the maturity model follows the development framework of (Bruin et al., 2005) and (Becker et al., 2009a). The maturity model was designed as a matrix with four unnamed maturity levels and the five relevant indicators. An assessment approach is proposed using either qualitative descriptions or a quantitative alternative. For the latter, the use of a Likert scale is proposed. It is not clarified in the paper how the proposed assessment alternatives can be applied.

(Seger et al., 2019) develop a maturity model framework specifically for intergovernmental organizations in their study. The maturity model describes a series of evolutionary stages that are passed through during their AI transformation and it consists of 5 maturity levels. The maturity levels are described. Essential influencing factors for AI application implantation are presented in the paper, but there is no indication of how they should be applied to each maturity level. Furthermore, it is not apparent how the individual maturity levels are to be evaluated in the course of determining maturity.

A maturity model was developed by (Alsheiabni et al., 2019) to assess the maturity of organizations that have already implemented or partially adopted AI. Therefore, according to the authors' own statement, the paper represents an attempt to develop an AI maturity model at the organizational level. The indicators were identified by the authors through an analysis of the general maturity model literature. The maturity model follows the design principle of (Becker et al., 2009a). It is represented by a matrix and includes 5 maturity levels and the corresponding 4 indicators identified from the literature. According to the author, an expert survey will be conducted in the future to validate the maturity model and, based on this, the maturity model will be further refined with case studies. Through further research in the scientific literature, it was not possible to determine whether this has already been implemented. No recommendations for action are given as to how the next maturity level can be reached.

(Gentsch, 2019) pursues the goal of developing a universally applicable maturity model based on an AI framework. The AI framework functions as an approach that captures the success factors and drivers of AI in companies and transfers them to operational applications. Building on this framework, a maturity model was developed that includes four maturity levels and five indicators described at each maturity level. The maturity model is intended to help companies assess their progress in AI based on the selected indicators and defined maturity levels. However, it does not provide details on how to evaluate these indicators, nor does it offer specific recommendations for action to reach a particular maturity level.

The maturity model of (Saari et al., 2019) was developed based on the maturity index of the Finnish Artificial Intelligence Accelerator (FAIA), an organization specializing in AI progress. Originally, the AI maturity index was first published in the 2018 Finnish Digibarometer. The resulting maturity model has been further developed and consists of five maturity levels described by six indicators. Each maturity level represents a prerequisite for the next. The questionnaire developed for the assessment assigns two questions with five response alternatives to each indicator, which are intended to reflect the maturity level.

The approach of (Kreutzer et al., 2019) is based on an AI maturity map. This maturity map serves as a tool to determine the maturity level and enables a clear distinction between the basic AI competencies and the specific application areas of AI in a company. The AI fundamentals are analyzed based on four indicators: AI goals, AI staff, AI systems, and AI budget. These indicators serve as guidelines to assess the current maturity level with respect to AI fundamentals. At the same time, the AI maturity map provides the flexibility to define the relevant application areas specifically for each company, as these may vary depending on individual requirements and goals. The five maturity levels are divided into percentages from 0% to 100% to show progress in terms of AI maturity. The indicators are evaluated equivalently by a percentage assessment from 0% to 100%. The advantages and disadvantages of self-assessment and third-party assessment are described in overview. Although the indicators are described roughly, the model does not explicitly specify how these indicators affect the individual maturity levels and how they should be evaluated as a result.

(Ellefsen et al., 2019) focus in their approach on how companies can successfully implement AI solutions in the areas of production and warehousing. In doing so, they propose to combine the maturity levels of AI with the maturity models of Logistics 4.0 in order to identify the relationship between the actual maturity level of logistics and the readiness of companies to implement AI solutions. The basis of the maturity model is a maturity model from the consulting firm Ovum, which places its focus on communications and media companies. The authors see great potential for applying this model to their problem, but do not substantiate this in the following. The model was adapted to meet the requirements of logistics and the use of AI in production and warehousing. Part of the work consisted of developing a questionnaire that was used to collect relevant information to determine the maturity level of companies. In total, the questionnaire includes 49 questions, but only 12 of them are presented in the paper. A case study was conducted in Norway and Poland and was based on direct interviews with the companies. The exact way of this maturity determination was not explicitly presented in this thesis, nevertheless the results were discussed.

(Lichtenthaler, 2020) proposes an AI management framework with five maturity levels in its maturity model, which is based on the five stages of autonomous driving. These allow consideration in terms of the degree of automation, which range from no automation to full automation. The AI management framework is intended to highlight untapped potential and unrecognized opportunities in virtually all companies by seeking to solve the additional opportunities of AI with the creation of an integrated intelligence architecture. The maturity model includes a total of 5 maturity levels, ranging from 1 to 5, and has been expanded to include the introduction of a "zero" maturity level and a higher-level future-oriented maturity level, but these are not explained in detail. The maturity levels are described. The three indicators: the different types of AI, the multiple aspects of human intelligence, and meta-intelligence are described, but not brought into the context of the individual maturity levels. No explicit approach to maturity assessment is presented.

(Yams et al., 2020) focus their work on how AI can and will change and support different aspects of innovation management. In developing the maturity model, the authors were guided by the development framework of (Bruin et al., 2005). The maturity model was designed as a matrix and consists of five maturity levels and six interrelated and interdependent indicators. To allow a more precise definition of the indicators, they were further specified by sub-indicators. The selection of indicators is based on the AI index developed by the consulting firm Gradient Descent. Although the model is described in detail, it does not include a specific scoring system for assessing AI maturity. The authors suggest that the development of an assessment tool could be considered in the future. According to the authors, this would serve to support the maturity model to enable a systematic assessment of a company's current AI maturity level. Through further research in the scientific literature, it could not be determined whether this has already been implemented. Furthermore, it should be noted that the authors do not provide any concrete recommendations for action on how to reach the next maturity level.

(Holmström, 2021) presents a comprehensive readiness framework designed to support the assessment of an organization's AI readiness. Four key indicators are defined that are used to assess the current situation and future expectations related to these indicators. The assessment is done through a self-assessment by employees, where they rate two statements per dimension using a Likert scale from 0 to 4. It is important to note, however, that the primary purpose of this maturity model is to perform an assessment and not to provide specific recommendations for action to achieve a particular maturity level.

(Limat, 2021) focuses in his research paper on the identification of corporate capabilities and characteristics that are relevant for the design of AI initiatives. The goal is to transfer these findings into a holistic maturity model. For this reason, a maturity model has been developed that enables a structured analysis of AI integration efforts at the enterprise level, based on different design domains. The development of this maturity model is based on the development frameworks of (Bruin et al., 2005) and (Becker et al., 2009a). A total of 18 sub-indicators were identified, which were subordinated to 7 main indicators. The description of the individual dimensions was done deliberately without weighting them. The focus is rather on a holistic assessment of the situation in order to comprehensively capture the integration of AI at the company level. The maturity model consists of 5 successive maturity levels, which are not discussed in detail. The indicators are not described at all levels.

In their research approach, (Mikalef et al., 2021) focus on identifying the organizational resources that companies need to develop their AI capabilities to achieve performance improvements. In doing so, they draw on the foundations of resource-based theory to determine an organization's AI capability. Through an in-depth analysis of existing academic studies and conducted interviews, the authors identify relevant technical and non-technical indicators that are critical to developing a company's AI capability. The identified indicators are divided into three categories and described in detail. Questions are defined that serve as measures to gauge a company's AI capability. The work of (Mikalef et al., 2021) focuses specifically on the impact of these indicators on business performance and creativity. It should be noted that the authors primarily address the identification and description of the indicators in their work and do not present a maturity model.

In their work, (Jöhnk et al., 2021) derive from scientific and practical literature the factors that influence a company's AI readiness and define relevant indicators for this AI readiness. Through this thorough analysis, they identified a total of five main indicators, which are in turn subdivided into 18 sub-indicators. These indicators are assigned AI characteristics and company-specific requirements. Maturity levels are not defined. The authors note that a comparison of organizational readiness factors for different technologies based on their underlying technological characteristics was not included in their work, but point out the benefits of such research. Furthermore, they suggest further research into the specific characteristics of organizations for AI adoption.

(Fukas, 2022) pursues the goal of an integrated management framework that combines insights from maturity model research with those from a comprehensive AI management perspective. In the development process of the maturity model, a systematic literature review was conducted at the beginning of the thesis and relevant indicators were defined. Furthermore, these indicators were assessed by experts by means of a questionnaire and a new model was created, which should cover all relevant aspects. The author is guided by (Becker et al., 2009a) in creating his maturity model. The nine indicators of the model are described in detail, but not in terms of the individual five maturity levels. The maturity model follows the design of a grid matrix and functions as an assessment model used to evaluate the state of an organization in terms of its AI capabilities. Control questions are designed to assess the state of the organization with respect to its handling of AI. Both the control questions and the associated assessment system are currently under (further) development and have not yet been fully elaborated. No concrete recommendations for action are given as to how the next maturity level can be reached.

The maturity model, developed by (Noymanee et al., 2022), focuses on maturity assessment of government organizations. The development process of the model involved a systematic literature review to identify relevant indicators. The model was designed according to the approach of (Becker et al., 2009a). It consists of 5 maturity levels and 5 main indicators presented in the form of a matrix and described at each level. The indicators are further subdivided into sub-indicators. However, no information is available on how the maturity level is determined for each indicator. No information will be provided on how to determine an overall maturity level. Furthermore, no concrete recommendations for action are given to achieve a higher level of maturity.

3. RESULTS

In accordance with SADIQ et al. (2021) Table 4 serves as a summary of the models, elucidating the key parameters. The table provides an overview of the Stages and associated indicators derived from the examined models, offering a consolidated and informative perspective on the factors considered for evaluating readiness-, capability- and maturity levels.

Table 4: Summery of the Models

Autor/s	*Number of Stages*	*Terms of the Stages*	*Number of Indicators*	*Terms of Indicators*
Alsheiabni et al. (2019)	*5*	*Initial, Assessing, Determined, Managed, Optimized*	*4*	*AI functions, Data Structure, People, Organizational*
Burgess (2018)	*6*	*Manual processing, Traditional IT enabled automation, Isolated basic automation attempts, Tactical deployment of individual automation tools, Tactical deployment of range automation, End-to-end-strategic automation*	*5*	*AI-Capabilities, Benefits, Existing Challenges, Strategic Objectives*
Ellefsen et al. (2019)	*4*	*AI novice, AI ready, AI proficient, AI advanced*	*5*	*Strategy, Organization, Data, Technology, Operations*
Fukas (2022)	*5*	*Initial, Assessing, Determined, Managed, Optimized*	*8*	*Technology, Data, People & Competences, Organization & Processes, Strategy & Management, Budget, Products & Services, Ethics & Regulations*
Gentsch (2019)	*4*	*Non-Algorithmic, Semi-Automated, Automated, Intelligence Enterprise*	*5*	*Strategy, Staff, Decisions, Data, Analysis*
Holmström (2022)	*5*	*None, Low, Moderate, High, Excellent*	*4*	*Technologies, Activities, Boundaries, Goals*
Jaaksi (2018)	*4*	*1, 2, 3, 4*	*5*	*Workforce, Data management, Process, Organization status, organizational maturity*
Jöhnk et al. (2021)	*N/A*	*N/A*	*5*	*Strategic alignment, Resources, Knowledge, Culture, Data*
Kreutzer & Sirrenberg (2019)	*5*	*0-20%: missing; 20-40% selectively present; 40-60% in individual areas, but not yet networked; 60-80% in many areas, networked to some extent; 80-100% completely networked in terms of content and structurally anchored in the company*	*4*	*Four Dimensions of AI-Basics: Objectives, Budget, Staff, Systems*
Lichtenthaler (2020)	*5 (+2)*	*(Isolated ignorance), initial intend, independent initiative, interactive implementation, interdependent innovation, integrated intelligence, (intuitive ingenuity)*	*N/A*	*Not available*
Limat (2022)	*5*	*1, 2, 3, 4, 5*	*7*	*Data, Culture, Competences, Strategy, Regulation, Customer behavior, Compatibility*

Mikalef & Gupta (2021)	*N/A*	*N/A*	*3*	*Tangible Resources, Human Resources, Intangible Resources*
Noymanee et al., 2022	*5*	*Rookie level, Beginner level, Operational level, Expert level, Mastery level*	*5*	*Strategy, People & Organization, Decision Making, Data and Analysis*
Saari et al. (2019)	*4*	*AI as part of identity, Integrated AI, Initial AI, Awareness of AI*	*6*	*Data, Technology, Internal Process, Product and Services, Competences, AI as a resource*
Seger et al. (2019)	*5*	*Unaware or risk averse, Aware and resourceful, Fully developed strategic plan, AI harnessed at scale*	*N/A*	*Not available*
Yams et al. (2020)	*5*	*Foundational, Experimenting, Operational, Inquiring, Integrated*	*6*	*Strategy, Ecosystem, Mindset, Organization, Technology, Data*

Source: Adapted from (SADIQ et al. (2021))

Following the analysis of the models, 102 different indicators and sub-indicators were identified. In accordance with Hizam-Hanafiah et al. (2020), an attempt is made to categorize these indicators into their main thematic areas. Indicators were considered for categorization when they exhibited differences in terminology and phrasing. The primary thematic categorization areas identified are Technology, Data, People, Strategy, Management/Leadership, Organization, External Influences, Resources, and not assignable indicators. The indicators were either assigned to categories based on the Description in their model or were implicitly categorized when explicit classification was not evident. Table 5 shows the allocation of all indicators to their respective domains.

Table 5: Concentration of the Indicators

Indicators	*Number*	*Assigned Indicators*
AI-Capabilities, AI functions, Technology, Analysis, AI as a Resource, AI-Systems, Scalability, Robustness, Democratization, Capability, Infrastructure & Technology, Digital Transformation	*12*	*Technology*
Data Management, Data Structure, Data, Data Readiness, Data Strategy, Data-driven Decisions, Data Quality, Integrated Data management, Data-Governance	*12*	*Data*
Workforce, People, Personal, Competences, AI-Employees, People & Skills, Technical Skills, Business Skills, AI Awareness, Upskilling, People & Competences	*11*	*People*
Strategic Objectives, Strategy, AI-Objectives, Vision, Value Creation, Governance, Goals, Commitment & Ownership, Imbedded Vision, Key Figures, Strategic alignment, AI-business potentials, Customer AI readiness, Top Management Support, AI-process fit, Data-driven decision making, Strategy & Management	*18*	*Strategy*
Product & Services, Operations, Mindset, Leadership, Change management, Process	*5*	*Management / Leadership*
Organization status, Organizational maturity, Organizational, Internal Process, Organization, Ecosystem, Collaboration, Communication, Impact, Innovation, Growth, Structure, Processes and operation aspects, Culture, agility, Innovation & Fault Tolerance, Talent, Training, Partner Network, Inter-departmental Coordination, Organizational Change Capacity, Risk proclivity, Innovativeness, Collaborative work, Organization & Processes	*25*	*Organization*
Existing Challenges, Boundaries, Regulation, Regulatory, Compliance & Ethics, Customer Behavior, Acceptance, Predictability, AI ethics, Ethics & Regulation	*10*	*External Influences*
Basic Resources, Resourses, Financial Budget, IT Infrastructure, Budget, AI-Budget, Staff	*7*	*Resources*
Decisions, Activities	*3*	*Not assignable*

Source: Adapted from (Hizam-Hanafiah et al. (2020))

Table 6 presents a comprehensive summary of the attributes discussed in the first chapter, providing a holistic view of their key characteristics and implications. In some of the examined models, the attributes were not explicitly stated. When possible, these characteristics were either implied or evaluated through subjective judgment. This was done to the best of our knowledge and judgment. If the evaluation of a particular characteristic was not feasible, it was omitted. In the case of combination of two characteristics, both were considered to emphasize their interrelatedness and significance. The information of the Design Principle (Top-Down, Bottom-UP) and the attribute assessment is based on the content of the respective sources from which the maturity models were extracted. Therefore, the table does not indicate whether the assessment method is possible, but rather how it is described. The evaluation of Design Principle is based on structure of the scientific work. That means, if the Indicators were defined before the maturity stages the model was evaluated as Bottom Up. Furthermore, it should be noted that only the maturity models contextually relevant to this study were evaluated and compared on a comparative basis. This means that certain maturity models might not have been accessible or were authored in a language different from the defined search-strings, and therefore. The assessment of novelty value is based on a subjective judgment and requires further elaboration. (Burgess, 2018) has been categorized as an innovation due to its chronological precedence as the first model of its kind. (Saari et al., 2019) was classified as an innovation because it introduced the first assessment system of its kind.

In the case of (Mikalef et al., 2021), although they not define a specific model, it stands out as the only study that conducted a thorough investigation of the indicators.

Table 6: Attributes of the Models

Characteristics		***Parameter Value***	*Burgess (2018)*	*Jaaksi (2018)*	*Seger et al. (2019)*	*Alsheiabni et al.*	*Gentsch (2019)*	*Saari et al. (2019)*	*Kreutzer & Sirrenberg*	*Ellefsen et al. (2019)*	*Lichtenthaler (2020)*	*Yams et al. (2020)*	*Holmström (2022)*	*Limat (2022)*	*Mikalef & Gupta*	*Jöhnk et al. (2021)*	*Fukas (2022)*	Noymanee et al.,
General attributes	*Institutional Background*	*Science*		*x*		*x*					*x*		*x*	*x*	*x*	*x*	*x*	*x*
		Individual	*x*				*x*		*x*									
		Company								*x*		*x*						
		Association or Society			*x*													
		Government Organization						*x*										*x*
	Novelty Value	*Innovation*	*x*					*x*							*x*			
		Variant								*x*		*x*						
		Version																
	Accessibility	*Freely Accessible*		*x*	*x*			*x*		*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*
		Cost-based	*x*				*x*		*x*									
		Consulting services																
	Priorisation	*No Priorisation*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*		*x*	*x*	*x*
		Priorisation possible													*x*			
		Priorisation Proposal												*x*	*x*			
		Adaptability																
	Target Group	*Management-oriented*				*x*		*x*		*x*	*x*	*x*	*x*	*x*		*x*	*x*	*x*
		Technology-oriented	*x*	*x*	*x*		*x*		*x*									
	Geographical Scope	*Yes*						*x*		*x*								
		No	*x*	*x*	*x*	*x*	*x*		*x*			*x*	*x*	*x*	*x*	*x*	*x*	*X*
	Breadth	*None-industry-specific*	*x*	*x*		*x*	*x*	*x*	*x*				*x*	*x*	*x*	*x*	*x*	
		Industry-specific			*x*					*x*		*x*						*x*

Model-specific Attributes	*Data Collection Technique*	*Interview*	x	x	x		x			x	x	x						
		Survey						x	x					x				
		Observation																
		Document Analysis																
	Assessment	*Self-assessment*	x	x				x	x		x		x	x				x
		Supported by third parties							x	x								
		Assessment by third parties																
	Tools	*None*	x		x	x	x		x	x	x	x		x			x	x
		Document-based											x		x	x		
		Computer-assisted						x										
	Maturity Level Definition	*Bottom-up*	x			x	x				x			x	x	x	x	
		Top-Down																x
	Purpose of Use	*Optimization*	X															
		Evaluation		x	x	x	x	x	x	x		x		x	x	x	x	x
General condition	*Empirical Foundation*	*No / Not documented*	x		x	x	x	x	x	x	x	x	x	x			x	x
		Documented, but no Case Studies		x											x	x		
		Case Studies								x								
		Empirical Foundation																

Source: Summary presentation of the results based on the sources mentioned above.

4. DISCUSSION

The comprehensive description and evaluation of the maturity models provide a solid information foundation, serving as a starting point for the discussion. The insights gained facilitate an examination of the various attributes and indicators of the maturity models.

4.1 The models in general

To ensure the relevance for the considered object, various approaches exist that allow for the step-by-step development of new maturity models (Akkasoglu, 2014). Many of the presented maturity models are based on the design frameworks proposed by (de Bruin et al. 2005), (Becker et al., 2009), and (Mettler, 2010). In his work, (Akkasoglu, 2013) critically examines existing approaches to the development of maturity models and questions their applicability to other domains. Akkasoglu argues that (Bruin et al., 2005) present a framework for creating maturity models in the context of process and knowledge management, and the transferability and applicability of this framework to other domains is unclear. Following this argument, the transferability to the field of AI should be discussed in the future. Additionally, the design framework proposed by (Becker et al, 2009) offers only limited support for the modeler of a maturity model. Both approaches do not provide a specifically developed maturity model, which makes validation more challenging or less transparent (Akkasoglu, 2013; Pöppelbuß et al., 2011).

Regarding the design of maturity models, (Sadiq et al., 2021) argue that the models use a bottom-up approach more often because artificial intelligence (AI) is no longer a new technology and is being used in various organizations. According to (Sadiq et al., 2021), this could explain the popularity of the bottom-up approach in the development of AI maturity models. A bottom-up approach, however, is characterized by the calculation of quality criteria or graphical interpretation. This allows potential maturity levels to be identified. The significant advantage of this approach, the high transparency and verifiability of the proposed developmental stages, is not evident in the maturity models (Winter et al., 2016).

4.1.2 Maturity Stages

The decision on the number of levels is mainly determined by weighing two factors. A small number of levels would have clear advantages for the model construction. Fewer levels mean less complexity and allow for a clearer definition of the developmental path. On the other hand, a large number of levels offers clear advantages for the application of the model. Many levels can achieve a broad differentiation, leading to a distinct differentiation between high-performing and low-performing organizations. This can be useful in the practical application of the model to enable a more precise and differentiated assessment and comparability. Most maturity models use 5 maturity levels, which can be seen as a compromise between these considerations. The labeling of maturity levels complicates or does not allow for adaptation and weighting possibilities within the practical applicability of a maturity model (Jording, 2018). Even when focusing on a specific application domain, it cannot be assumed that maturity levels in different maturity models precisely represent the same concepts (Maier et al., 2011).

4.1.3 Recommendations for action

Regarding the assessment of maturity levels and the associated recommendations, mainly descriptive models were identified, and only two of the examined maturity models included an assessment tool. (Saari et al. 2019) and (Holmström, 2022) are the only two maturity models that include an assessment tool, enabling the evaluation of maturity levels. In both maturity models, two questions are used for determining the maturity level for each dimension and stage, but they differ in the type of assessment. Holmström (2022) employs a quantitative approach using a Likert scale, while Saari et al. (2019) uses pre-defined answers. In this context, the appropriateness of an assessment system based on a few questions to comprehensively evaluate a complex system comes into question. No information was found in the literature to assess the breadth and depth of a questionnaire. It can be argued that such a system may provide initial insights, but it might not be able to adequately capture all relevant aspects. (Ellefsen et al., 2019) mentioned a developed questionnaire in their work, but it is not fully disclosed in the publication.

4.1.4 Geographical Scope

Regarding the geographical scope, specific geographic restrictions are generally not taken into account during the development process. The scope is primarily defined by the framework of the empirical investigation (Jording, 2018). (Saari et al., 2019) developed their maturity model for Finland, while (Ellefsen et al., 2019) applied their maturity model in Norwegian and Polish companies. In both models, no dependency on geographical factors is apparent.

4.1.5 Terminology

(Sadiq et al., 2021) delve into the terminologies used in the models and how they differ across various models. In this context, the focus is on the terminology used in the models in general, considering their overall terminology and not specific to any particular model. Both readiness models and maturity models have been presented. The definitions of terms used in these models require thorough clarification to ensure a clear understanding. According to (Holmström, 2021), "readiness" is defined as the "capability" to implement AI in the organization. Readiness is defined in the literature as the question of whether the company is "ready" for AI deployment in its operational environment. Therefore, the concept of readiness is context-dependent. To achieve readiness, the AI system must be validated against user requirements (Tetlay et al., 2009). In their work, (Jöhnk et al., 2021) follow this approach and are able to clearly differentiate the concept of readiness. The introduction of AI requires a thorough understanding of relevant AI readiness factors and a tailored alignment between the organization's current AI readiness and the intended purpose of AI adoption. In (Saari et al., 2019), readiness appears to assess maturity, in turn determining readiness itself. Based on this statement, it could be inferred that the concept of "maturity" is embedded within the concept of "readiness" (Tetlay et al., 2009). In contrast, according to (Ellefsen et al., 2019), the assessment of readiness takes place before the actual development process to examine whether the prerequisites for the maturity process are met. On the other hand, the maturity assessment occurs during the maturity process to capture the current state of development and evaluate progress. According to (Tetlay et al., 2009), maturity involves the evaluation within an iterative process and occurs before readiness. This implies that the system must first be fully "mature" before it can be considered "ready" for deployment. To address these challenges and enable cross-sector and cross-domain initiatives related to AI, it is important to establish common terminologies and definitions. A shared terminology and understanding of key concepts can serve as a foundation for communication and collaboration in the models (DIN, DKE, 2022).

4.1.6 Relevance and Applicability

A crucial influencing factor for achieving reliable maturity models is the maturity of the object under consideration. However, this aspect is often overlooked, impacting the usability of the maturity models. The newer the domain of the object under consideration, the more significant the uncertainty in practical application, and the higher the need for a maturity model. Conversely, the newer the domain, the less widespread it is, which is reflected in the reliability of a maturity model (Mettler, 2010). In the future, a technological roadmap for AI developments could play a significant role in aligning technological advancements with requirements and needs. This involves fostering the establishment of solution spaces (e.g., catalogs) for patterns of requirements and creating the possibility of a framework for classifying AI methods. Additionally, semi structured application scenarios could be formulated, from which potential AI methods can be derived to address and consider these use cases in the maturity levels (DIN, DKE, 2022).

(Kreutzer et al. 2019) oppose the enterprise prerequisites to the AI applications in their maturity model. (Gentsch, 2019) takes these aspects into account by comparing technologies and AI methods with use cases. (Burgess, 2018) contrasts AI applications with enterprise benefits and hurdles. However, the impact of requirements on the maturity levels is not apparent. In the future, the innovative concept of AI engineering could create a modular approach that provides clear definitions and establishes conditions under which AI solutions are appropriately applicable (DIN, DKE, 2022).

4.2 Indicators

When considering the evolutionary development of indicators in maturity models, it becomes evident that over time, more and more influencing factors have been taken into account. Additional indicators, such as ethics and regulations, have been introduced as the field progressed. The number of indicators varies significantly across different maturity models. While a comprehensive analysis of all indicators is is not the scope of this paper, two specific indicators were selected: data and costs. This selection is based on their significance in the maturity models themselves and their frequent mention in the general literature on AI applications.

The indicator "data" was chosen because it was identified as one of the most commonly used indicators in the analyzed maturity models. The effective implementation of data analytics tasks is significantly influenced by the methods and algorithms used. These algorithms often have specific requirements for the data, which should be appropriately considered within the framework of a maturity model. All maturity models focus on a holistic implementation of AI. Therefore, the "data" indicator is seen more as a means to an end, which is considered from various perspectives in the maturity models. However, none of the examined maturity models sufficiently analyze the specific requirements placed on the "data" indicator from the perspective of AI applications (Bernerstätter, 2019). By initiating the ISO/IEC-5259 standard series, which is still in development, a common framework is established in the field of data quality for AI to describe terminologies and data quality management processes across sectors (DIN, DKE, 2022).

The second indicator "Costs" was selected due to its frequent mention as a hindrance in the literature. In an extensive literature analysis conducted by (Merkel-Kiss et al., 2022), numerous publicly available studies were examined to identify hindrances related to maturity models. Taking various factors into account, it was found that the human factor, including skilled labor shortage and lack of competencies, along with the aspect of effort, particularly in terms of costs, were the most commonly mentioned obstacles. The indirect consideration of costs is achieved by incorporating financial resources (Jöhnk et al., 2021). Although the maturity models by (Kreutzer et al., 2019) and (Fukas, 2022) do not explicitly introduce a cost indicator, this aspect is implicitly described through the indicator of the budget. However, during further research, no scientific work was found that specifically examines the costs of common AI applications. Despite the lack of explicit cost indicators in the mentioned maturity models, works like (Seger et al., (2019) have proposed a factor called "Return on Artificial Intelligence," which aims to compare the benefits of AI with the associated costs. It is not evident how this factor is incorporated into the model or how it can be assessed.

4.2.1 Reflective vs. formative characteristics

In the examined maturity models, the formative and reflective characteristics of the indicators are not explored. (Mikale et al., 2021) do not define a maturity model in their work, but they made a distinction of the indicators based on their formative and reflective characteristics. The reflective model specifies the effects and impacts of a model on its indicators. On the other hand, the formative model specifies the indicators as causes of a model (Bollen et al., 1991). In the maturity models, it is not evident whether a change in the indicators leads to a change in the maturity level or vice versa (Jarvis et al., 2003). The maturity model proposed by (Yams et al., 2020) emphasizes the mutual dependency of the indicators, but an investigation of these dependencies is not presented in their work. Similarly, in the work of (Noymanee et al., 2022), the dependence of the "Data" indicator is evident but not mentioned or explored. If mistakenly reflective indicators are used, it does not result in an incorrect model, but rather a significantly restricted model. This means that the substantive content of the construct is narrowly defined. Only the simultaneous changes in drivers are tested for their impact on success, leaving the question of whether individual drivers make independent contributions to success unanswered (Albers et al., 2006).

4.2.2 Prioritization and weighting of the Indicators

The independence of individual indicators not only serves as a basis for their weighting but also allows for separate evaluation and potential customization of the maturity model (Jording, 2018). It is advisable to differentiate the indicators based on their relevance to the defined goal of the maturity model. This can be achieved through weighting the indicators, with higher weights assigned to those that are particularly significant for achieving the model's objective (Akkasoglu, 2013). Among the examined maturity models, the concept of weighting the indicators is only present in the work of (Mikalef et al., 2021). To enhance the robustness and practicality of maturity models, further research should be dedicated to exploring different approaches to determine indicator weights based on their significance and impact on the overall assessment. It is not to be assumed that all the factors underlying the assessment of an object make an equal contribution to the performance of the object. Furthermore, it should be considered that the significance of the assessed content may vary depending on the specific circumstances and conditions of the organization (Jording, 2018).

5. CONCLUSIONS

Overall, this paper demonstrates that maturity models can serve as an instrument for assessing and improving AI readiness and maturity. To fully leverage their potential from the user's perspective, these models could be further developed specifically for AI solutions, designed transparently, and include a user-friendly assessment approaches. With these improvements, maturity models can contribute to further advancing AI implementations in businesses and pave the way for effective and responsible utilization of AI technologies.

In his work, (Akkasoglu, 2013) critically examines existing approaches to the development of maturity models and questions their applicability to other domains. Akkasoglu argues that Bruin et al. (2005) present a framework for creating maturity models in the context of process and knowledge management, and the transferability and applicability of this framework to other domains is unclear.

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