Designing an Artificial Intelligence Maturity Model for Human Resources (HR-AIMM)

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Abstract: Artificial intelligence (AI) has the potential to change the world of work radically. Wherever information processing is involved, AI can be integrated into processes with added value. From the perspective of Human Resource (HR) management, this implies three things: first, business models and performance processes in the company will undergo change; second, employee requirements will change; and third, HR processes will change. While the literature describes various AI maturity models, there has been no dedicated consideration of HR management. This article, therefore, aims to identify relevant influencing factors for an AI-orientated approach to HR management and to describe these in more detail using maturity levels in a Human Resources Artificial Intelligence Maturity Model (HR-AIMM). The resulting HR-AIMM consists of eleven dimensions. These include anchoring the AI topic in the corporate and HR strategy, its use in selected HR processes, considering ethical, data-related, and infrastructural principles, and organisational, cultural, and competence-related anchoring. The characteristics of these factors enable the identification of four maturity levels for using AI in HR management: from a curious start to the level of holistic integration. Our framework supports researchers and companies in understanding and evaluating the factors influencing the professional application of AI in HR management.

Keywords: Maturity model, Artificial intelligence, Human resources, HR-Management, AI capability, AI readiness

1. Changing the World of Work Through Artificial Intelligence

Artificial intelligence (AI) has the potential to radically change the world of work (Franken and Wattenberg, 2019). The overwhelming interest in this technology can be seen, among other aspects, in numerous previous attempts to define it (see Palos-Sánchez et al, 2022). Haenlein and Kaplan (2019, p. 1) view AI as "*a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation*".

Since the race to improve generative artificial intelligence became public with ChatGPT, the extent of the potential changes has become increasingly apparent. The economic opportunities are enormous: McKinsey calculates that generative AI, in particular, has a value potential in the range of USD 6.1 - 7.9 trillion – a result that can be attributed to new use cases on the one hand and to productivity increases among employees on the other (Chui et al, 2023).

Accordingly, there is a high interest in implementing AI in organisations.

At the same time, there are massive implications for work processes and workforce structures: Generative AI will replace a proportion of working hours in all jobs. Hazan et al (2024) have calculated that, on average, generative AI can replace 27% of the hours employees work. The more administrative and routine-based a job is, the more likely AI will substitute parts of the activity. Occupations characterised by standardised information processing are also at risk (Eloundou et al, 2023). Overall, companies assume that just as many jobs will be created through AI as will be lost (Hays, 2024).

Human Resource (HR) management faces two challenges in this change situation: Firstly, it must actively support the integration of AI into company processes and structural and skills-related changes within the company – as a change agent, organisational and HR developer, and strategic partner to management. Secondly, it must adapt its processes, structures, tools, and competencies considering the possibilities of AI-supported HR work.

It is precisely because HR management has a role model and pioneering function due to its role in supporting change that it is necessary to take a closer look at the company's own AI introduction and implementation processes.

This is where maturity models (MM) step in, enabling companies to assess and monitor their status quo in a specific domain (Alsheiabni et al, 2019; Wendler, 2012). The main idea of an MM is "*that it describes in a few phrases, the typical behaviour exhibited by a firm at a number of levels of maturity, for each of several aspects*" (Fraser et al, 2002, p. 244).

Despite considerable interest from scholars in the development of AI-related maturity models, there needs to be a greater understanding of the dimensions and maturity levels relevant to the specific domain of HR.

For this reason, this article aims to close this gap by operationalising relevant dimensions for using AI in HR and transferring them into an MM (HR-AIMM).

Therefore, the aim is to develop and transfer an MM with the dimensions of influencing factors that need to be considered in the professional implementation and application of AI in HR management.

In close accordance with previous research on MM (e.g. Fukas et al, 2021), the underlying questions of this study are:

RQ1: Which dimensions and components represent the influencing factors for the HR domain concerning the implementation of AI technologies?

RQ2: How can the dimensions and components be described using maturity levels and mapped in a modular, multidimensional maturity model?

The remainder of the paper is structured as follows: First, Chapter 2 addresses the state of research on AI maturity models. This is followed by a description of the method in Chapter 3 and the presentation of a model in Chapter 4. The paper concludes with a discussion in Chapter 5 and a conclusion in Chapter 6.

2. Related Work

The related work has been organised into two main sections. The first summarises HR and AI literature, and the second focuses on the MM approach to AI.

2.1 Human Resource Management

For some time now, companies have recognised the relevance and inevitability of AI in HR to adapt to rapidly changing conditions and withstand competitive pressure.

Boselie et al (2021, p. 484) emphasise that "*HRM involves management decisions related to policies and practices that together shape the employment relationship and are aimed at achieving certain goals"*. Therefore, while Boselie et al (2021) focus on management decisions and their influence on the employment relationship and thus emphasise the strategic orientation of HRM to achieve organisational goals. HRM is often operationalised as a combination of different HRM practices that shape employee relations within and outside the organisation (Boselie et al, 2021).

The application of AI in HRM is an emerging field with continuous growth and a promising outlook for the future (Palos-Sánchez et al, 2022). AI is reshaping processes in almost all critical areas of HRM and is increasingly being integrated into various operational HR processes (Tambe et al, 2019).

Current areas of HRM AI applications can be found throughout the entire employee life cycle, starting with recruitment, selecting suitable candidates, onboarding, performance management, training and development, and retention (Kaushal et al, 2023). Various AI-based technologies, such as automated systems, personal assistants or chatbots, can be used. A study of HR professionals confirms that 89% already use AI tools in their HR departments. The most common use case is generative AI systems such as ChatGPT in recruitment and hiring processes (59%). Overall, communication with human contact persons is being severely restricted (Greenhouse, 2023).

Advanced digital technologies such as AI create added value and cost efficiency, for example, by facilitating management decision-making through an expanded range of knowledge (Kumar et al, 2022). Although AI can thus optimise all phases of HRM, there are numerous challenges that HRM must face when implementing AI (Palos-Sánchez et al, 2022; Tambe et al, 2019). These include managing the overall impact of AI on employees (A. Malik, 2023), leadership resistance (Frick et al, 2021), human rights and ethical challenges regarding data privacy and discrimination (Stahl et al, 2023).

2.2 Maturity Models

The research literature uses the terms "*maturity*" and "*readiness*" as starting points for developing models.

Maturity generally refers to a system's progress towards a target state, defined by a series of successive stages.

AI readiness, in turn, refers to "*the preparedness of organisations to implement change involving applications and technology related to AI*" (Alsheibani et al, 2018, p. 3).

Depending on the authors, "*readiness"* is seen as preceding, synonymous, embedded or context-dependent to "*maturity"* (Reichl and Gruenbichler, 2023).

Although there is great interest in maturity models (MM) in the research landscape, only a few authors provide a definition. Pullen (2007, p. 9) defines MM as a "*structured collection of elements that describe the characteristics of effective processes at different stages of development [and] also suggests points of demarcation between stages and methods of transitioning from one stage to another*".

An MM thus describes the typical development paths of an object class by mapping development stages, from the starting point at the lowest level to full maturity at the highest level in the domain under consideration (Becker et al, 2009). As a result, MMs are helpful tools for describing a specific domain's status, potential and requirements (Wendler, 2012). They allow organisations to monitor the step-by-step development within an implementation process, leverage the capabilities of a particular domain and increase its strategic potential (Alsheiabni et al, 2019; Bruin et al, 2005). They serve as a starting point for future growth, identify necessary steps and potential transition challenges, and help prioritise. Through generally accepted growth stages, they enable the definition of progress and the measurement of improvements compared to other organisations (Pullen, 2007). Therefore, MMs are a strategic tool for continuous comparison and roadmap development (Fukas et al, 2021).

Furthermore, MMs can be classified according to various characteristics. Bruin et al (2005) distinguish between three application-related purposes of MMs: 1) Descriptive: evaluation of the current state, 2) Prescriptive: normative models that offer specific recommendations for action and guidelines for growth, 3) Comparative: models with which companies can be compared internally and externally. In addition, the scope of MMs can be general or domain-specific and can differ according to the level of analysis (company, department, people, projects, system, process, object) (Sadiq et al, 2021). The model itself can be structured cyclically or iteratively, whereby the degree of maturity can be measured qualitatively or quantitatively as well as discretely or continuously (Kohlegger et al, 2009). However, according to Sadiq et al (2021), standardised terminology for modelling (e.g. dimensions, constructs, elements, indicators) has yet to be established despite numerous MMs.

Even though MMs are widely represented in the research literature, this number decreases considerably with an additional increase in specificity and a reference to AI.

Lichtenthaler's (2020) framework offers an initial approach in which the author presents five maturity levels of AI management. In addition, Saari et al (2019) developed an AIMM to evaluate the maturity level of different departments in the company. The conceptual AIMMs by Alsheiabni et al (2019), Limat (2022) and Jaaksi (2018) are located at the organisational level. The same applies to Schuster et al (2021), focussing on small and medium-sized enterprises. Holmström (2022) and Jöhnk et al (2021) form a framework with indicators that characterise the readiness of companies, although Jöhnk et al (2021) do not define maturity levels. The "*3-horizon model"* by Kreutzer and Sirrenberg (2020) is to be understood as an AI maturity map, which also considers fields of application and should serve as a starting point for a company's own AI journey. Other AIMMs relate to the domains of marketing (Gentsch, 2019), innovation management (Yams et al, 2020), logistics (Ellefsen et al, 2019), manufacturing (Sonntag et al, 2024) and auditing (Fukas et al, 2021).

In addition, developing maturity models is a highly competitive market to which various organisations such as market analysts, consulting companies and software providers are committed. AIMMs from these sources include ElementAI (2020), appliedAI (2021), Accenture (2022), MITRE (2022), DFKI (2022) and Deloitte (2024). Despite lacking scientific documentation, the advantages of using AIMMs from these organisations may include greater practical suitability and (online) self-assessments.

Despite presented AIMMs cover several different domains, a significant research gap remains: To the authors' best knowledge, no study currently addresses the domain of HR, though this is crucial for a holistic understanding of a company's maturity.

3. Method

The procedure of the present study is based on the steps widely accepted and used in research for the development of a MM by Becker et al (2009), which is based on the Design Science Research Approach. In addition, the recommendations of Bruin et al (2005) are included in the development (fig. 1). The approach is therefore presented using a linear logic with strong interdependencies.

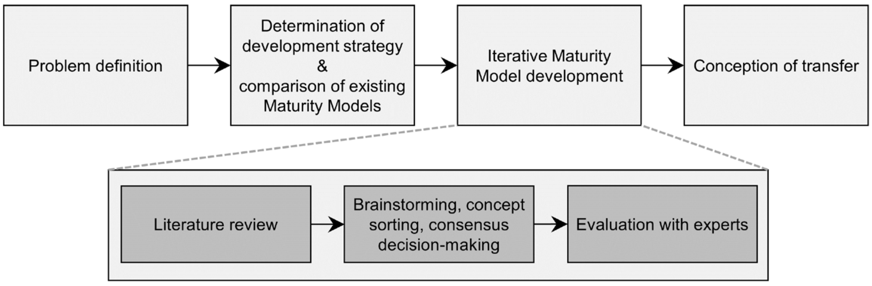

Figure 1: Steps of MM development based on Becker et al (2009) and Bruin et al (2005). Source: Author's own work

3.1 Problem Definition

According to Becker et al (2009) the initial stage of the process involves defining the problem, which includes identifying the targeted domain and target group, discussing the relevance of the problem and the anticipated benefits, and determining the conditions for applying the model. With this in mind, HR was defined as the target domain. The intended MM aims at HR managers and company executives. Next, it is necessary to outline the research objectives and formulate key questions. Finally, there is the need to concentrate on refining its functionality, effectiveness, and clarity, thereby validating the conditions necessary for its application.

3.2 Determination of Development Strategy and Comparison of Existing Maturity Models

Since, to the best of the authors' knowledge, no MM for AI could be identified in HR at the time of the study, we follow the procedure for developing an entirely new MM according to Becker et al (2009).

3.3 Iterative Maturity Model Development

This process step's objective was the fundamental development of the model, including the definition of the modelling approach, the elements, and the validation.

Regarding the modelling approach, a prescriptive model with a multidimensional structure was chosen due to its high relevance, transferability into practice, and the expected complexity. As there was no HR-AIMM and, therefore, no preliminary basis for the development of the model, a top-down approach was chosen in which the maturity levels are developed first and subsequently the items of assessment (Bruin et al, 2005).

For the development of the elements, this study is based on the sub-processes of Rigamonti et al (2024), including literature research, knowledge-generating techniques, and validation.

In the first sub-process, the existing literature must be analysed (Becker et al, 2009). In a first step, existing systematic literature reviews (SLR) of AIMMs were researched, and the works of Sadiq et al (2021) and Reichl and Gruenbichler (2023) were identified. Cited studies included in both SLRs were combined and analysed for cardinality: $|A \cup B| = |A| + |B| - |A \cap B|$ with A=SLR(A) and B=SLR(B). Given that the vast majority of literature on the development of AIMMs also contains SLRs for existing MMs, further AIMMs were identified following a forward and snowball search. In the second step, we conducted our research using a slightly formalised narrative review using the search term (*"artificial intelligence maturity model" AND "human resources")* and its German translation on Google Scholar and Google. The reason for this approach is that previous SLRs have lacked the results of the efforts of numerous practice-oriented organisations and institutes due to their methodologically rigorous selection of research literature. According to this paper's authors, however, including these sources with a practical perspective is decisive for developing a transferable MM. In the third step, identified studies were compared in tabular form based on the dimensions and maturity levels used. While a complete review of AIMMs is beyond the scope of this article, Chapter 2.2 already outlined several examples. Finally, a synopsis was created.

Various knowledge-generating techniques were used as the following sub-process (McGraw, 1989). Following Rigamonti et al (2024), several brainstorming sessions with the research team were held to identify dimensions and maturity levels for a preliminary MM. Concept-sorting, a technique in which participants sort categories according to their subjective similarity, was used to structure dimensions, subdivide them into further components, and assign maturity levels. Finally, consensus decision-making was used to achieve agreement among all participants, favouring solutions supported by all participants.

The final sub-process relates to evaluating the formulated maturity levels (Becker et al, 2009) to ensure the validity of the content. To this end, a qualitative research study was conducted with six HR and training experts from different industries. The experts were selected based on their professional experience, personnel and organisational development knowledge, and digitalisation topics. They received the maturity levels for written assessment and were evaluated according to expression, comprehensibility, clarity, appropriateness, and differentiation criteria. They were also able to leave detailed comments. The written feedback was analysed using a qualitative content analysis. Moderated discussions were held via Zoom, during which the ratings and comments were discussed and documented. The analysis of this documentation revealed strengths and weaknesses of the maturity levels, particularly concerning complexity, technical language and unclear terms. Suggestions for clarification were developed. Feedback on the appropriateness of the maturity levels about the practical requirements was also included.

3.4 Conception of Transfer

The final step is to define the transfer medium (Becker et al, 2009). For this purpose, an interactive website was created that enables companies to determine their level of maturity of AI implementation in HR by answering a questionnaire. In addition, presenting results in a radar chart allows benchmarking with comparable companies (Armutat et al, 2024).

4. Structure of the HR AI Maturity Model

The HR-AIMM consists of eleven dimensions with two items each (see Table 1) and four maturity levels (cf. 4.1).

4.1 Maturity Levels

The following maturity levels were defined:

- Curious start: Companies have not yet undertaken any activities relating to the integration of AI in HR management.
- Learning experimentation: Companies are experimenting with AI-supported systems for selected groups of people or in individual areas of HR management.
- Project-related implementation: Companies already have initial experience with the task- or project-related introduction of AI-supported systems in HR management.
- Holistic integration: Working with AI systems is established and anchored in various areas of HR management within the company.

4.2 Dimensions

Table 1 below presents the dimensions and components:

Table 1: Description of dimensions. Source: Author's own work. Note: Core dimensions were summarised due to identical items and thus do not accumulate to 11

Dimension (d)	Item (i)	Differentiation by maturity level (m1-m4)
People and culture	Change Management	change management is (1) no topic yet, (2) has been considered, (3) planned or (4) established
	Participation	employees are (1) not informed, (2) informed, (3) partially involved or (4) involved in collaborative, cross-functional teams for further development
AI in corporate strategy	Role of AI	(1) AI plays no role, (2) is being experimented with, or whether (3) strategic projects have been initiated or (4) established
	Attitude of the management	the company management (1) has not positioned itself, (2) is open to experimentation, (3) demands AI measures or (4) has firmly established them
Data Management	Data collection and data utilisation	data collection and data use have (1) not yet been addressed, whether the prerequisites (2) are being worked on or whether a DMS (3) has been implemented and (4) automated
	General conditions	regulations are (1) not in place, (2) planned, (3) occasional or (4) extensive

Ethics	Conception of AI guidelines	guidelines are (1) not in place, (2) planned, (3) introduced or (4) established with compliance processes
	Integration of AI guidelines	measures for compliance with AI guidelines are (1)not in place, (2) planned, (3) introduced or (4) established
Infrastructure	Use of AI technologies	AI technologies are (1) not in use, (2) researched, (3) under development or (4) implemented
	Required hardware	the necessary hardware (1) is known, (2) is being procured and (3) has been partially or (4) fully implemented
AI in HR strategy	Relevance	AI is (1) no part of the HR strategy, (2) experiments with AI in individual HR tasks are strategically anchored, (3) strategic AI projects for selected HR processes are anchored, (4) AI-based HR processes are a central component
	Competence status of employees	employees have (1) no, (2) partial or (3) full competencies and (4) develop these further
Competence development	Competence profiles	necessary changes in skills are (1) unknown or (2) analysed, and whether target profiles have been (3) partially or (4) fully derived
	Development of AI-related competencies	development measures are (1) available, (2) planned, (3) partially or (4) entirely realised
Organisation	Processual anchorage	processes are (1) undefined, (2) partially, (3) coordinated or (4) fully integrated
	Personal responsibility	a responsibility is (1) non-existent, (2) project-related, (3) temporary or (4) permanent
AI in HR recruitment, HR deployment, HR development	Experience	there is (1) no, (2) experimental, (3) task-related or (4) optimised experience
	Attitude	HR stakeholders are (1) negative or (2) open to AI and (3) share experiences or (4) are experienced in its use

4.3 Visualisation and Calculation

The MM can be visualised as a box model in which some dimensions can be structured based on our findings in such a way that they serve as a framework for other dimensions (Figure 2).

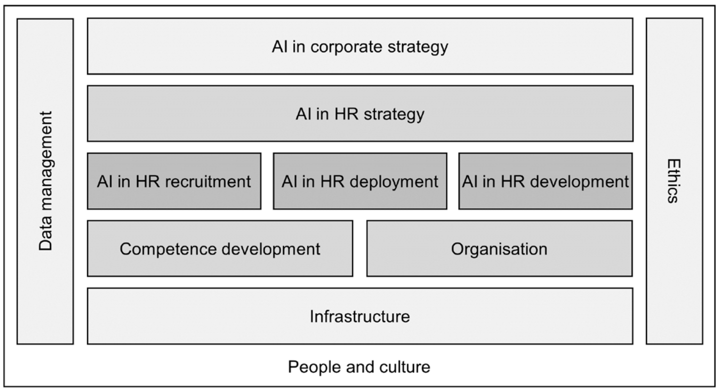

Figure 2: Multidimensional maturity model with framing and independent dimensions. Source: Author's own work

However, there are only slight interdependencies between the dimensions, which means that the level of development in one dimension does not necessarily influence or condition the maturity in another. This allows independent assessment and further development of each dimension, which promotes flexibility and adaptability in implementing and applying the model. Nevertheless, a distinction between supporting dimensions in three layers and exclusive HR core dimensions can be made. The maturity level of all dimensions is calculated using the function:

$$M_{model} = \sum_{d=1}^{11} \sum_{i=1}^{2} m_{(d,i)}$$

Whereby:

d: Dimension index with $d \in \{1,2,\ldots,11\}$.

i: Item index within one dimension, with $i \in \{1,2\}$.

m: Maturity level of an item, whereas $m_{d,i}$ represents the maturity level of item i in dimension d with $m_{d,i} \in \{1,2,3,4\}$.

The average maturity level is therefore calculated as follows:

$$\bar{M} = \frac{M_{model}}{D \times I}$$

5. Discussion

5.1 Practical Contribution

The maturity model has a wide range of possible applications in companies. Understood as an operationalised maturity level assessment, it helps decision-makers in the company to analytically determine the status quo that needs to be considered in the implementation process. At the action level, activities necessary to create the conditions for the successful introduction of AI in HR management can be derived - be it data-related challenges or, for example, the development of the competencies of the relevant stakeholders. With this help, the model can support project planning and help to identify appropriate work packages. Secondly, the model helps to develop a perspective for AI integration in the HR management strategy: Relevant strategic target areas come into view based on a holistic strategic approach that gives equal weight to structures, competencies and cultural framework conditions. Thirdly, it could be a continuous periodic indicator of how HR management is developing in the direction of AI. This allows culturally sensitive and transparent introduction processes to be planned and implemented. Involving the workforce promotes the acceptance of AI applications and the maturity check can be used for introduction processes beyond HR management.

5.2 Theoretical Contribution

To the authors' knowledge, the proposed MM is the first HR-AIMM described in the scientific literature. This closes a remarkable research gap and offers researchers numerous reference points.

5.3 Limitations

Our study is subject to certain limitations frequently encountered in the development of MMs: It focuses on the actual state and the potential, while specific recommendations for action to achieve the following maturity levels can only be derived from the description of the items. In addition, the interdependencies of the dimensions shown in the box model were only validated to a limited extent and can, therefore, only be regarded as initial indicators. As interdependencies become more critical with the increase in complex organisational skills, this is a particular opportunity for further follow-up research.

6. Conclusion

The article shows which influencing dimensions need to be considered in the professional implementation and application of AI in HR management so that the use of AI systems increases the success of the HR function. The systematic analysis, including MMs on the market and the evaluation, ensures that the maturity levels are theoretically sound, practically relevant, and understandable. The framework can be mapped in a practical questionnaire that interested individuals or HR managers can complete. In this way, it helps companies to systematically analyse the status quo of AI requirements and use in HR management and thus provides orientation for the strategic development of technically supported HR work. ollow-up research may also feel particularly encouraged to address the interdependencies between dimensions, as these become increasingly important with the growth of complex organisational capabilities.

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The proposed maturity model can be assessed via an online self-assessment at https://hr-aimm.com.

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