Generative AI Competencies: Framework and Maturity Model for Users in Their Work Settings

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Abstract: The increasing use of generative artificial intelligence (GenAI) is changing work processes in companies and requires new competencies from employees. While existing competency models primarily focus on general AI, they do not sufficiently account for the unique features of generative systems. The aim of this article is therefore to develop a specific AI competency framework and maturity model for the successful and reflective use of GenAI in a corporate context. Based on a design science approach, relevant skills were tested for their transferability, supplemented with GenAI-specific competencies, and operationalized along defined maturity levels. A consultation with experts was conducted to evaluate the model. The result encompasses three competency areas – digital/technological, social, and cognitive competencies – with a total of 18 individual competencies, mapped to three maturity levels of GenAI use in companies. The model supports researchers and practitioners alike in systematically assessing competency levels within companies, identifying potential areas for improvement, and developing targeted strategies for competency development.

Keywords: Generative AI, GenAI literacy, GenAI skills, GenAI competency framework, GenAI maturity model

1. Introduction

Generative AI (GenAI) currently requires companies to make future-oriented adjustments at all levels of corporate management. Whether in terms of business models, operating models, tasks, or processes, machine-supported systems that operate autonomously to varying degrees, can adapt to their environment, and are thus able to generate predictions, content, recommendations, or decisions and influence their working environment (BITKOM, 2024) are currently demonstrating their eruptive potential more and more clearly. According to McKinsey, GenAI has a value potential of US$6.1–7.9 trillion, achieved through new use cases and different ways of working, as well as associated productivity gains among employees (Chui et al, 2023).

This is already having noticeable consequences: GenAI is increasingly becoming an integrated tool that is changing the nature of work. Studies estimate that GenAI could replace up to 27% of the hours worked in companies; the proportion of replaceable working hours is particularly high in administrative jobs, which are often dominated by standardized routines (Hazan et al, 2024). Changes are emerging not only in the type of tasks but also in how tasks are performed: collaboration is becoming more agile, tasks are becoming more self-organized, and work settings are becoming more hybrid. This requires employees to develop new skill sets to perform effectively in a changing work environment. These skill sets include AI literacy, but above all, skills that help employees navigate the changing corporate landscape, such as social and emotional skills, cognitive skills like analytical thinking, and project management, which also play significant roles (Hazan et al, 2024).

The use of GenAI has not only triggered these changes but also has an impact on how they are managed. Specifically, this means that the use of GenAI in a business context not only requires collaboration based on the principles of agile project management techniques, for example, but also that this AI-induced agile collaboration is shaped by the options offered by AI applications in practice. This idea of the dual impact of GenAI on tasks and their management is not taken into account in most AI competency frameworks.

This is where the present work comes in.

The aim is to answer the following main research question: How does AI, and especially GenAI, influence the work-setting-related competency frameworks according to its dual impact on tasks and work behaviour? The two derived research questions are:

RQ1: What competencies do employees need in their work setting to use GenAI effectively and efficiently to accomplish their tasks, some of which have been changed by GenAI?

RQ2: How can the characteristics of these competencies be described in terms of maturity levels and mapped in a modular, multidimensional maturity model?

The first objective is to create a generic AI-competency maturity model that aligns with the requirements of work-integrated GenAI use and serves as a framework for companies to modify their own competency models. The target audience comprises users of GenAI in a corporate context and is thus deliberately distinct from IT specialists or AI developers. The second objective is to contribute to scientific competence modelling research through the AI-dual impact thesis, which should stimulate in-depth research on the competence-inherent influences of AI.

The remainder of the paper is structured as follows: Chapter 2 addresses the theoretical foundation. This is followed by a description of the underlying methods in Chapter 3 and a presentation of the model itself in Chapter 4. The paper concludes with a discussion and conclusion in Chapter 5.

2. Theoretical Foundation and Related Work

First, a differentiation is required between AI literacy and AI competencies, which are often used synonymously in the literature but are linked rather than identical.

According to Chiu (2025), AI literacy refers “to a foundational conceptual understanding of AI [and] focuses on knowledge, critical thinking, and ethical awareness rather than technical skill” (p. 3225). It thus enables individuals to use AI responsibly, question results, recognize limitations, and make informed decisions (Chiu, 2025).

AI competency refers to the practical ability to utilize AI systems in real-world contexts, interact with them, develop them, or manage them, and thus extends beyond mere knowledge and understanding (Chiu, 2025; Zhou et al, 2025). At its core, this competency involves retrieving relevant dispositions for the situational problem at hand and combining them into action. It thus plays a decisive role in determining a person's future ability to act in new contexts, resulting in situational performance. For this process to be successful, the person must be able to reflect on, adapt, and expand their dispositions in action, which, in turn, enables agile adaptability and the ability to deal with uncertainty (Spöttl, 2011).

Overall, AI literacy refers to the knowledge and understanding of AI, whereas AI competency encompasses the higher-level ability to apply this knowledge to achieve results (Chiu, 2025).

Campion et al (2011) developed the “Framework for competencies”, a reference framework for analysing and identifying competencies, based on the approaches used by a wide variety of organizations for competency modelling. In their definition, they refer to “competency models [...] as collections of knowledge, skills, abilities, and other characteristics (KSAs) that are needed for effective performance in the jobs in question” (Campion et al, 2011, p. 229). On this basis, a cascading determination of relevant competencies within an organization is carried out. Based on this, a company-specific, generic competency model is then derived. Various methods of requirements and job analysis are used to derive a job family-specific competency model from this generic, holistic competency model. Finally, these competencies must be operationalized through measurable behaviours so that the model can be applied to operational human resources work.

Maturity levels refer to the progress of a system toward a target state defined by a series of successive stages.

Maturity models (MM) are then defined by Pullen (2007) as “a structured collection of elements that describe the characteristics of effective processes at different stages of development [and] also suggest points of demarcation between stages and methods of transitioning from one stage to another” (p. 9).

MM thus describe the typical development paths of an object class by mapping the sequence of development stages – from the starting point at the lowest level to full maturity in the considered domain (Becker et al, 2009). They capture the current status, existing potential, and specific requirements of a domain (Wendler, 2012) and, through generally accepted growth stages, enable progress to be defined and improvements to be measured (Pullen, 2007). In this way, they support organizations in pursuing gradual development within implementation processes, systematically utilizing existing capabilities, and enhancing their strategic potential (Alsheiabni et al, 2019; Bruin et al, 2005). MM can therefore be considered a strategic tool for future growth by identifying necessary actions and potential transition challenges, facilitating the prioritization of areas for action, and enabling a roadmap for the company's further development (Pullen, 2007).

Although the research literature extensively addresses AI literacy (Chui, 2025), research on GenAI competencies is still in its early stages. Annapureddy et al (2025), for example, formulate 12 general competencies for GenAI, covering essential skills and areas of knowledge required for interacting with GenAI, ranging from “basic AI literacy” to the ability to engage in continuous learning. As a special feature, the competencies follow a logical sequence to reflect continuous learning in the sense of a learning path. The authors see their literature-based model primarily as a starting point for further research on application and implementation in government and organizations.

Other researchers are developing domain-specific GenAI competency frameworks. Anica-Popa et al (2024), for example, divide the competencies required for accounting and audit professionals into cross-disciplinary skills and profession-specific competencies. In the education sector, in contrast, students must develop GenAI competencies, which consist of application, authenticity, accountability, and agency (Cardon et al, 2022). Furthermore, Burneo-Arteaga et al (2025) developed a GenAI competency framework for higher education that encompasses the domains of GenAI, responsible AI, and pedagogy, with a total of 16 competencies for educators.

The influence of GenAI on the competencies of postgraduate students was addressed by Aladsani (2025). Students developed several competencies, grouped into four key areas: technical and AI competencies, ethical and legal competencies, critical thinking and analytical competencies, and lifelong learning and interpersonal competencies.

Regarding AI maturity models, industry-related models from consultancies (e.g., AppliedAI, 2021) and academic models are becoming increasingly established, with domain-specific models gaining prevalence. These range, for example, from applications in logistics (Ellefsen et al, 2019) to manufacturing (Sonntag et al, 2024) or HR (Armutat et al, 2024). GenAI has also been mapped in maturity models primarily by consultancies and technology companies (e.g., Ey, 2024) to support companies during implementation. However, these models typically focus on individual aspects such as technology and lack empirical evidence (Banh, 2025). Given the nascent state of GenAI research, academic contributions are limited to a few models. For example, Banh (2025) presents a preliminary model for the organizational adoption journey consisting of the five key dimensions (i.e., capabilities): (i) people, (ii) process, (iii) technology, (iv) data, and (v) organization. Skills and competencies are part of the people dimension.

Overall, it can be noted that existing literature does not offer any competency-related frameworks within the context of maturity models for GenAI. Furthermore, no studies could be identified that integrate the aforementioned reciprocal relationship between the competency requirements for GenAI and their influence on competencies.

3. Method

The approach to designing the GenAI competency framework follows a linear logic based on the steps for developing an MM, as outlined by Becker et al (2009), which has proven its practical suitability (Armutat et al, 2024).

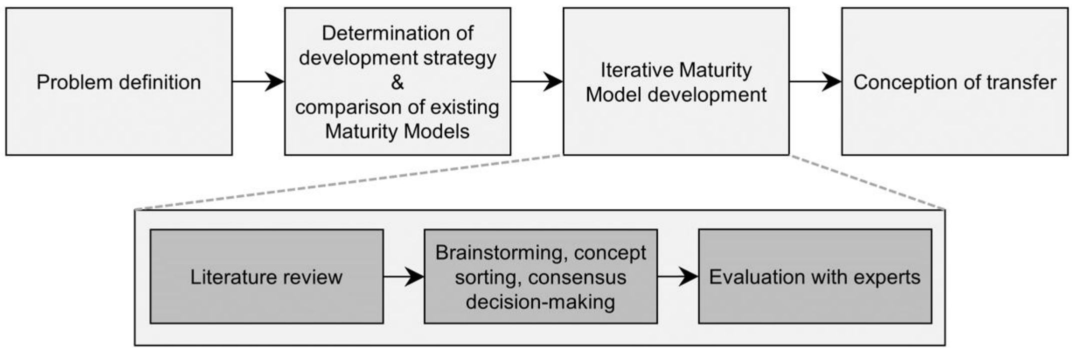

Figure 1: Steps of MM development (Armutat et al, 2024), based on Becker et al (2009) and Bruin et al (2005)

According to Becker et al (2009), the initial phase of the process is dedicated to *problem definition*, encompassing the identification of the domain and target group, the examination of the problem's relevance and anticipated benefits, as well as the specification of the conditions under which the model is to be applied. The target domain and target group of the MM being pursued are the HR sector, specifically HR managers and executives at companies. Additionally, it is necessary to define the objective and the underlying research questions (cf. Chapter 1). Finally, functionality, effectiveness, and comprehensibility must be improved to create the necessary conditions for application.

Regarding the determination of development strategy, a prescriptive model was chosen because significant complexity was anticipated and a high degree of transferability to practice was targeted. Since previous GenAI competency frameworks do not account for the reciprocity described above – competencies are required for the use of GenAI, which in turn influence the competencies – a top-down approach is pursued, in which the maturity levels are first defined. Then the assessment items are developed (Bruin et al, 2005). The AI competency framework developed by Franken et al (2022) was used to develop the dimensions, as it has proven to be remarkably versatile and practical. The framework draws on the core areas of digital, cognitive, and social competencies, which, in the authors' opinion, also represent a promising basis for the use of GenAI, as confirmed by the new studies cited above.

Iterative MM development is divided into three sub-processes, based on the approach outlined by Rigamonti et al (2024), which involve literature research, knowledge-generating techniques, and validation.

The *literature review* was conducted less formally due to the limited number of relevant publications on GenAI competency and the novelty of the topic. Instead, a non-systematic, comprehensive literature review of studies in English was conducted, based on targeted searches in Google Scholar and Google to identify both academic and practice-oriented contributions.

The next sub-process involved using various *knowledge-generating techniques* based on the evaluated literature (McGraw, 1989). This included several brainstorming sessions with the research team to identify items and stages of development, concept sorting to structure items within the proposed dimensions and assign maturity levels, and consensus decision-making to reach a consensus on the maturity level assignments.

The following *evaluation* involved experts from corporate practice, associations, academia, and labor unions, each with proven expertise in the subject area, to ensure the model's valid applicability. These included two company representatives (the head of corporate learning at a multinational corporation and the head of human resources), a scientist specializing in the field of competency mapping, and a union representative with expertise in the human-centred introduction of digital technologies in affiliated companies. Their feedback was integrated through several iterative loops and fed into the preceding sub-processes to refine the model further.

The final step involved the *conception of transfer* and thus defining the transfer medium. The results of the process (model, description, maturity levels) were documented in tabular form (cf. Section 4.2) and visualized in the form of a radar chart (cf. Section 4.3). For this reason, an online format is particularly suitable for reaching the broadest possible target group. The research group's homepage on the university website and the overarching joint project's website (cf. Acknowledgements) were identified for this purpose. Additionally, posts were written on LinkedIn, and joint project partners were informed via email.

4. GenAI Competency Framework

The resulting model describes three levels of maturity in working with GenAI in a corporate context and is based on 18 individual competencies that are classified into three overarching dimensions (digital/technological, social, and cognitive competencies).

4.1 Maturity Levels

The characteristics of these competencies enable the differentiation of three maturity levels in dealing with GenAI in a corporate context. These levels of maturity describe the development from initial engagement with GenAI to its reflective and efficient integration into existing work processes:

- *Maturity level 1:* “I am just starting to explore and experiment with generative AI.”
- *Maturity level 2:* “I am systematically experimenting with generative AI to accomplish selected tasks, and I learn from my experiences.”
- *Maturity level 3:* “I have fully integrated generative AI into my work context, and I use it efficiently and reflectively to accomplish my tasks. I support the professional use of AI in my organization.”

The maturity levels were chosen to reflect a practice-oriented learning journey; in particular, maturity level 1 was deliberately defined as the operational starting point and formulated in a competency-oriented manner to highlight typical challenges when starting out, without depicting them as incompetence.

In the following section, the competencies are assigned to the three maturity levels and described in terms of their respective characteristics.

4.2 Dimensions

This section describes the three dimensions of the model (digital/technological, social, and cognitive competencies) in detail. For each dimension, the associated individual competencies are named and described along the three maturity levels (m1–m3). The development of competencies is presented in tabular form, illustrating how the use of GenAI progresses from initial steps to routine application and ultimately to strategically reflective integration in the work context.

Item (i) and description	m1	m2	m3
AI technology competency: Understanding of technical contexts and generative AI capabilities.	Knows basic terms such as AI, algorithm, model.	Understands the operating principles of general AI applications such as training, probabilities, hallucinations.	Can explain how it works, its limitations, and its impact on work processes in a well-founded manner, acts as a multiplier among colleagues.
Use case competency: Selection of suitable AI tools for the specific work context.	Knows individual AI tools and their general areas of application.	Can differentiate several tools and name suitable use cases.	Actively identifies new tools, evaluates them strategically, and develops appli-cation strategies for oneself and the team.
Application competency (prompting): Effective input and further processing of AI outputs.	Formulates simple queries and uses basic functions.	Creates precise prompts, optimizes results, identifies weaknesses.	Uses complex prompting techniques, strategically structures dialogues, automates tasks, shares experiences with colleagues.
Data and information competency: Critical examination of AI results based on the underlying training data.	Is aware of the possible existence of errors and recognizes obvious errors caused by data biases.	Understands data-based biases and checks content for subtle errors or biases in this context.	Has an objective review process and applies it systematically and regularly to validate AI content, supports colleagues with similar questions.
Security competency: Protection of sensitive data and prevention of data protection violations.	Is aware of the existence of fundamental data protection rules (e.g., GDPR, EU AI Act).	Distinguishes between secure/insecure applications, knows company policies.	Proactively implements security concepts, develops them further, and raises awareness among others.

Figure 2: Description of the three maturity levels of digital/technological competencies in dealing with GenAI. Source: Author's own work

Item (i) and description	m1	m2	m3
Critical reflection: Verification of plausible-appearing AI-generated content for accuracy, consistency, and unbiasedness about the work context.	Accepts AI output largely without reflection. Rarely detects errors, distortions, or inappropriate content.	Critically reviews AI results on a case-by-case basis. Begins to question the plausibility and consistency of content in relation to the work context.	Regularly and systematically considers the content, context, and limitations of AI. Integrates reflection as an integral part of work processes and raises awareness of the topic among colleagues.
Ethical awareness: Awareness of the implications of AI-generated content about discrimination and responsible reflection on its use, among other things.	Hardly considers the ethical consequences of using AI-generated content; uses AI and AI-generated content without reflection.	Takes fundamental ethical aspects (e.g., data protection, fairness) into account when using AI and AI-generated content, depending on the situation.	Considers the ethical implications of AI use from the very beginning; helps shape standards and AI guidelines for ethically sensitive AI use; raises awareness among others.
Learning ability: Ability and willingness to acquire the necessary skills to use evolving AI applications.	Reacts hesitantly to new AI tools and concepts. Has few developed strategies for AI-supported independent learning.	Learns selectively and reactively through trial and error, using AI. Independently searches for information when needed and develops initial learning routines.	Learns continuously and strategically with the help of AI. Adapts learning processes flexibly to new developments and supports others in AI-based learning.
Problem-solving competency: Ability to analyze tasks in a structured manner, break them down into solvable sub-problems, and identify suitable application scenarios for AI.	Rarely recognizes where AI can help with real-world problems; tends to use it in a playful manner or according to instructions.	Utilizes AI to handle specific tasks. Links tool functions to problems.	Develops creative, well-thought-out solution strategies using AI; systematically analyzes problems and plans AI-supported solutions in consultation with colleagues.
Process thinking: Understanding of processes and inter-relationships to use AI not only selectively, but also embedded in work processes.	Sees work tasks in isolation. Realizes little potential for integrating AI into processes.	Sees work tasks in the context of operational processes. Recognizes initial potential for supporting processes with AI.	Systematically uses AI to map processes and further develop the process landscape.
Creativity and innovation: Using AI to develop new solutions, products, and ideas.	Is inspired by new ideas when using AI coincidentally and reactively.	Uses AI to generate new ideas and concepts as the situation demands.	Systematically combines AI with creativity techniques to develop new ideas and concepts; supports colleagues with their own experience.
System knowledge: Understanding of how AI architectures work, data protection regulations, legal frameworks, and technical dependencies.	Uses AI as a black box without understanding the technological or legal foundations.	Understands basic system dependencies (e.g., training data, copyright, API usage).	Actively recognizes and considers complex technological, regulatory, and organi-zational dependencies when working with AI; acts as a multiplier among colleagues.
Holistic thinking: Awareness of the holistic implications of using AI in a business context.	Views AI usage more as a technical tool for work environments, without considering organizational implications.	Recognizes occasional implications of their own AI use in specific situations and takes this into account when performing their work.	Systematically considers the technical, social, and organizational implications of AI use, creates conditions for AI application appropriate to these implications, and acts as a multiplier.

Figure 3: Description of the three maturity levels of cognitive competencies in dealing with GenAI. Source: Author's own work

Item (i) and description	m1	m2	m3
Communication competency: Ability to use AI to improve one's own communication and to communicate the evaluation of AI results clearly, comprehensibly, reflectively, and in a manner appropriate to the target group (in dialogue).	Uses generative AI occasionally to improve their own communication and phrasing; finds it difficult to explain AI results.	Increasingly uses generative AI as a tool for more complex tasks, such as writing and editing emails and simple translations. Increasingly communicates with colleagues about content, benefits, and limitations.	Systematically integrates generative AI into communication processes (e.g., for automated translations and text optimization). Communicates efficiently and in a target group-oriented manner with AI support.
Ability to work in a team: Ability to share generative AI across roles to collaborate constructively on tasks.	Generative AI is rarely used within the team. Team communication and coordination traditionally take place without AI support.	Uses generative AI as needed when collaborating with colleagues, for example for brainstorming or creating team documents. Discusses AI-generated results and gradually learns how to efficiently integrate AI support into collaboration.	Integrates generative AI firmly into teamwork, for example, through automated protocols and joint brainstorming, supports the efficient AI-assisted completion of routine tasks, and the sharing of knowledge.
Interdisciplinary and intercultural cooperation: Using AI solutions together across disciplinary and cultural boundaries, incorporating different perspectives on AI.	Interaction with other disciplines or cultures takes place mainly without AI support. Has difficulty dealing with other disciplines and cultures or perspectives in relation to AI.	Exchange with other disciplines or cultures takes place on an event-related basis with AI support. Cooperates constructively across disciplinary and cultural boundaries, respects different AI perspectives.	Actively uses generative AI to optimize interdisciplinary and intercultural colla-boration. Actively builds bridges between disciplines, cultures, and people, integra-ting diverse perspectives into AI projects.
Ability to handle mistakes: Identify errors or inaccuracies in AI, analyze them systematically, and systematically learn from them.	AI results are accepted uncritically; systematic verification hardly ever takes place. Errors or inaccuracies in AI are rarely reflected upon or corrected.	Recognizes the error-prone nature of generative AI and specifically checks AI results. Corrects errors and learns from them by adjusting inputs (prompts) and procedures.	Utilizes generative AI to specifically detect and correct errors. Systematically analyzes sources of error and uses the findings to continuously improve processes; errors are viewed as learning opportunities, and AI-supported checks are integrated into quality assurance.
Change management: Supporting employees and organizations through the changes brought along by AI and actively shaping change processes.	Is rather skeptical and passive toward new AI tools; change processes are usually initiated by others and there is a lack of initiative. New technologies are only accepted reactively, depending on operational possibilities, and hesitantly.	Shows openness to AI-driven change and actively participates in it. Tests new AI tools depending on the company's capabilities, supports transformation projects, and contributes initial experience with AI to their design.	Proactively drives change processes with the help of generative AI, both for themselves and their colleagues. Initiates the introduction of new AI technologies, makes learning with AI an integral part of the work culture, and supports colleagues in the work process.
Project management: Plan, manage, and complete projects in a structured process using generative AI, taking into account time, budget, and quality.	Plans and manages projects primarily manually without AI support. Project plans and risk assessments are created traditionally.	Uses generative AI tools to support project management, e.g., for initial schedules, risk assessments, or meeting summaries.	Fully integrates generative AI into project planning and management. Plans resources, schedules, and budgets with AI support, creates automated status reports, and uses continuous analysis to identify risks early on and adjust projects efficiently.

Figure 4: Description of the three maturity levels of social competencies in dealing with GenAI. Source: Author's own work

4.3 Visualisation and Calculation

The MM is visualized as a three-dimensional radar chart. There are only minor interdependencies between the dimensions, as the development status of one dimension does not necessarily affect the maturity of other dimensions. This allows all dimensions to be evaluated and developed independently of one another, which supports flexibility and adaptability in the model's implementation and use.

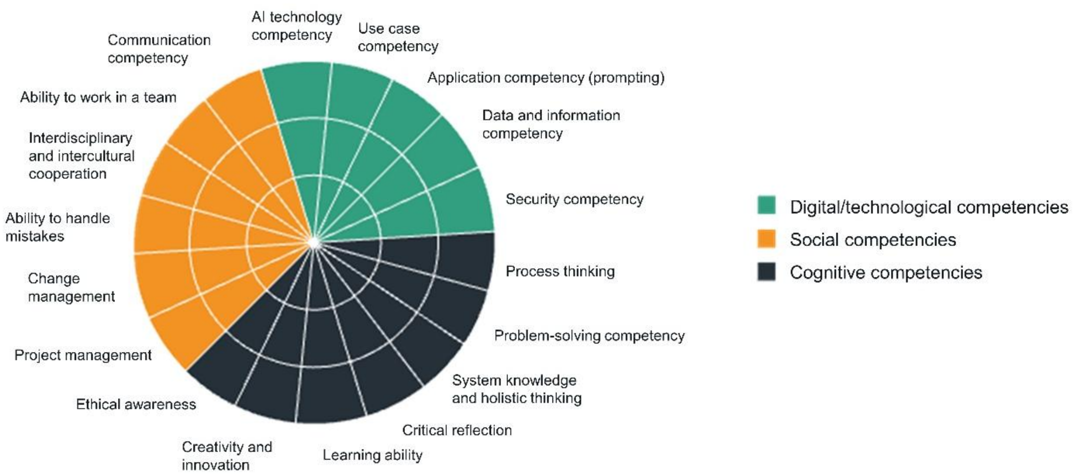

Figure 5: GenAI-competency maturity model with independent dimensions. Source: Author's own work

The overall maturity score M of the model was calculated as the mean of all 18 items, each rated on a scale of 1 to 3. The items are grouped into three dimensions (i = 1,2,3) with n_i items each ($n_1 = 5$, $n_2 = 6$, $n_3 = 7$). Formally, M can be expressed either by dimension or using a sequential index k:

$$M = \frac{\sum_{i=1}^{3}\sum_{j=1}^{n_i} r_{ij}}{\sum_{i=1}^{3} n_i} = \frac{\sum_{k=1}^{18} r_k}{18}$$

Here, r_{ij} denotes the maturity level of the j-th item in dimension i ($r_{ij} \in \{1,2,3\}$), and r_k the maturity level of the k-th item across all dimensions. This approach aggregates the maturity of all dimensions into a single score ranging from 1 to 3.

This also means that the three dimensions of the model are treated equally (none is given special preference or weighting), as the overall maturity level is calculated as the average of all items. Each category, therefore, contributes to the overall result in proportion to the number of items it contains.

5. Discussion and Conclusion

The AI Competency Maturity Model offers companies a systematic framework for identifying, structuring, and developing the specific skills that employees need to utilize artificial intelligence in their work in a reflective, effective, and efficient manner. By focusing on users of GenAI in a corporate context, the model deliberately distinguishes itself from IT specialists or AI developers, whose competencies could not be adequately captured in the selected dimensions and would therefore need to be considered in a separate model. This makes the model manageable and directly applicable to the competency development of the broad workforce.

The model creates the opportunity to expand existing competency models to include AI-related dimensions. This facilitates connectivity to established HR and development processes, ensuring the company's competency landscape remains up-to-date and future-proof.

Additionally, the model enables companies to assess their employees' existing AI competencies transparently. It allows for a differentiated assessment of the current situation, both within individual departments or teams and in comparison with other organizations or industries. Such comparisons are not only valuable for internal personnel development but also promote benchmarking and interorganizational learning processes.

Another key benefit is the ability to create individual competency profiles and derive development plans accordingly. This allows AI-related competency development measures to be tailored precisely to the specific needs of individual employees. This enhances the effectiveness of learning opportunities, boosts motivation, and accelerates strategic competency development.

At the same time, the model combines the perspectives of a competency model and a maturity model: while competencies provide the content basis, maturity levels describe the characteristics and development of these competencies in the context of their application. The chosen three-stage classification represents a practical, understandable, and compatible solution that promotes acceptance among managers and employees, even if empirical validation is still pending and further refinement remains to be conducted.

Overall, the AI competency maturity model thus serves as a bridge between human resources research, technological developments, and individual competency development. It helps to make companies future-proof and prepare the workforce for the demands of an increasingly AI-permeated working world.

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The proposed maturity model can be downloaded via the project's website https://arbeitswelt.plus/.

Ethics declaration: Expert feedback was obtained as part of the conceptual development process. As participation was voluntary, non-sensitive, and limited to professional expertise, no formal ethical approval was required.

AI declaration: In writing this article, the authors utilized DeepL and Grammarly to support the writing process and enhance the linguistic presentation of their thoughts. However, the ideas, concepts, and arguments presented in this article are solely those of the authors.

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