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Empirically Grounding and Refining a Model for Teachers' AI-Related Competences: Insights from Expert Interviews

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Abstract: The growing adoption of artificial intelligence (AI) in education is reshaping teaching and learning in schools, while also increasing the professional demands on teachers. To support effective and responsible AI use in schools, a clear and empirically grounded understanding of teachers' AI-related competences is required. This study examines and refines an existing competence model by incorporating perspectives from diverse stakeholder groups. Seven semi-structured expert interviews were conducted with representatives from computer science, educational science, subject-specific didactics, schools, industry, and education policy. The data were analysed using structured qualitative content analysis to identify relevant competence dimensions and their interrelations. The findings largely support the overall structure of the model but place particular emphasis on the central role of AI didactics. AI-related competences are not limited to technical understanding or tool use but crucially involve the ability to design, implement, and reflect on learning processes with and about AI. This includes selecting meaningful use cases, adapting instructional formats, addressing ethical and societal implications, and developing new approaches to assessment and classroom practice in response to AI. In addition, personal and social dispositions for effective AI use and teaching about AI in everyday school practice function as enabling conditions for the enactment of these competences. Based on these results, the model was elaborated to provide an empirically grounded, didactically actionable framework for teacher education and future research.

Keywords: *AI competences, competence model, teacher education, qualitative content analysis*.
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Introduction

The use of AI tools in education is increasing among both students (Bitkom, 2025) and teachers (Bitkom, 2024; OECD, 2025). At the same time, many teachers feel insecure when working with AI tools (Robert Bosch Stiftung, 2025). The increasing availability and functionality of AI systems are simultaneously changing teaching and learning processes in schools, thereby expanding the professional demands placed on teachers (Holmes et al., 2023; Jaschke et al., 2023). To address this insecurity and the changing AI-related demands, it is essential to develop teachers' AI-related competences in initial and continuing teacher education so that teachers can use AI confidently and foster corresponding competences among students (Seyferth-Zapf et al., 2025). This requires a theoretically grounded specification of the competences teachers need to design learning processes with and about AI in a subject-appropriate, responsible, and learning-effective manner.

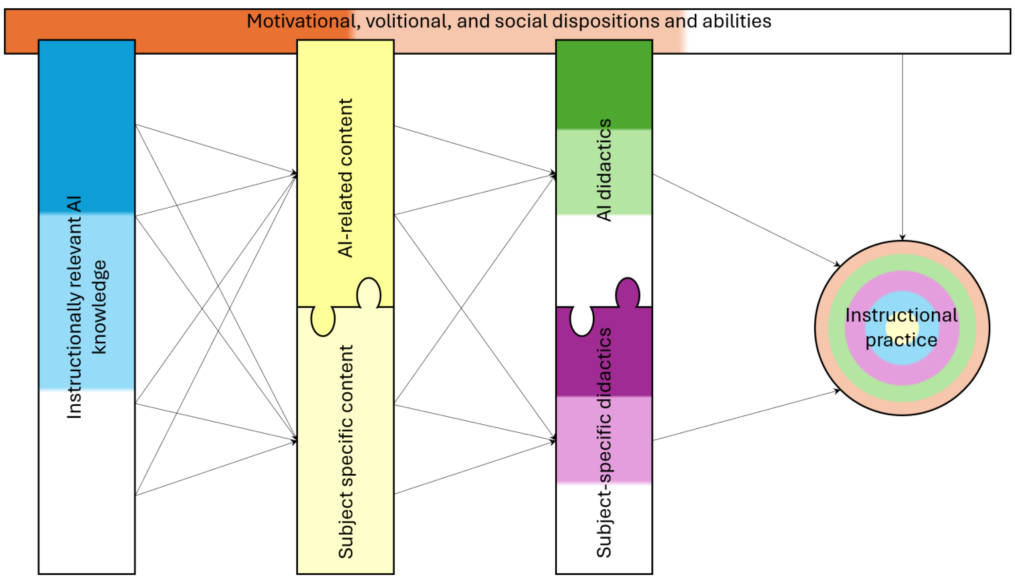
In order to define these competences, it is necessary to distinguish AI-related competences from other concepts, such as AI literacy, digital competence, or data literacy. First, digital competence with frameworks such as DigCompEdu (Redecker, 2017) or DPACK (Döbeli Honegger, 2021; Thyssen et al., 2023) conceptualise teachers' professional abilities in using digital technologies for teaching, learning and assessment, thereby offering a broad and well-established foundation for technology-related and digital competences in education. However, these frameworks do not explicitly address the specific characteristics of AI systems, such as their probabilistic nature, opacity, or autonomous decision-making, nor the resulting instructional implications (Mikula, 2026c). While AI-related competences can be understood as a specialised extension within digital competence and therefore as a necessary prerequisite (Ng et al., 2023; Wang et al., 2023), they require additional knowledge and skills that go beyond general digital competence, and should therefore be considered separately from digital competences (Laupichler et al., 2023). In comparison, data literacy focuses on the ability to collect, analyse, interpret and critically reflect on data (Calzado-Prado & Marzal, 2013; Raffaghelli, 2019). While it is relevant for understanding certain aspects of AI, particularly those related to training data, bias, and data-driven decision-making, it does not sufficiently capture all relevant aspects of AI-related competences. AI literacy, lastly, is defined in the context of education as the skills needed to understand, evaluate, and apply AI systems for teaching and learning (Delcker et al., 2025; Long & Mangerko, 2020). While this concept shares important overlaps with AI-related competences for teachers, particularly regarding understanding and critical reflection, the focus in literacy is typically on the application-specific and domain-specific perspectives and less on the instructional design, subject-specific didactics, and the general integration of knowledge, abilities, skills, motivations, and volitions (Falloon, 2020; Le Deist & Winterton, 2005; Weinert, 2001). Taken together, these perspectives highlight that AI-related competences for teachers constitute a distinct, profession-specific competence domain that integrates elements of digital competence, data literacy, and AI literacy, but extends beyond them by explicitly addressing the requirements of teaching and learning with and about AI.

However, existing AI-related competence models only partially cover the need of integrating AI related competences into educational contexts and neglect relevant dimensions, as shown by Mikula's (2026c) scoping review. Most models, such as Intelligent-TPACK (Celik, 2023) or SNAIL (Laupichler et al., 2023), primarily address cognitive aspects, including technical, ethical, and pedagogical knowledge and the use of AI tools. At the same time, dimensions of teaching and learning about AI, as well as motivational, volitional, and social dimensions, remain underrepresented (Mikeladze et al., 2024; Mikula, 2026c). Since AI is used across all subject areas and should therefore be addressed in all disciplines, teachers of all subjects should be able to teach and learn about AI to foster students' AI-related competences (Delcker et al., 2025).

Against this background, Mikula (2006c) developed a structural model of teachers' AI-related competences based on a systematic scoping review of approximately 4000 international articles, including a comparative analysis of 17 AI-related competence frameworks for teachers (Figure 1). It systematises core knowledge and action domains and highlights gaps in existing competence models, especially regarding AI-didactics. At its core is instructionally relevant AI knowledge, including basic functional principles and the reflective, responsible use of AI applications. Building on this, the model distinguishes content knowledge comprising both subject-specific disciplinary knowledge and AI-specific content knowledge required to position and address AI as a learning object. As a next step, pedagogical competences differ between subject-specific didactic competences that remain relevant regardless of AI and AI didactics addressing learning organization and instructional logic in AI contexts. Complementing these are motivational, volitional, and social dispositions (e.g., attitudes, willingness, and professional relationship management), considered indispensable for successful implementation. Those four layers together lead towards good instructional practice. Each of those layers has progression levels, so that the level of competence can be made clearly visible (Bloom, 1956). Overall, the model provides an integrative framework that combines disciplinary, pedagogical, and technical requirements for teaching and learning with and about AI.

Figure 1

Mikula's competence model



Note. From Mikula (2026c)

To date, the model is purely theoretical, leaving open which competence dimensions are considered relevant by different stakeholder groups (e.g., educational research, subject didactics, or industry), and whether additional aspects need to be integrated. To avoid restricting responses to the assumptions of the current framework, empirical insights are required that capture stakeholder perspectives in an open manner. Expert interviews provide a suitable methodological approach, as they capture experience- and interpretation-based knowledge from diverse professional perspectives and support the structuring of AI-related competence requirements for teacher education (Bogner et al., 2014; Reinhold, 2015). Accordingly, this article aims to develop and empirically ground the proposed competence model by first eliciting stakeholder views and subsequently comparing and integrating them with the model derived from the scoping review. Therefore, the study addresses the following research questions:

- RQ1: Which AI-related competences do (prospective) teachers need for teaching and learning with and about AI, and how can these competences be defined according to experts in the field?
- RQ2: How should a competence model be designed that covers the specific requirements of teaching and learning with and about AI while integrating the key technical and pedagogical dimensions needed for effective AI use?

Methodology

Research Design

This study builds on a competence model that was previously developed through a systematic scoping review synthesising the international research on teachers' AI-related competences (Mikula, 2026c). The review provided a comprehensive conceptual basis, outlining relevant knowledge domains, pedagogical and didactic dimensions, and personal dispositions associated with the use of AI in educational contexts. The present study aimed to further elaborate and empirically ground this model by integrating practice- and experience-based perspectives from key stakeholder groups.

Therefore, a qualitative study was conducted, analysing semi-structured expert interviews using structured qualitative content analysis (Kuckartz & Rädiker, 2023). Reporting followed the Consolidated Criteria for Reporting Qualitative Studies (Tong et al., 2007). Expert interviews are particularly suitable for exploring interpretation-based knowledge rooted in professional experience and for gaining insights into how competence requirements are understood across different domains (Reinhold, 2015). Experts were purposively selected through targeted searches and contacted via email and defined as individuals with documented professional or academic expertise related to AI in subject-specific didactics, schools, educational science, computer science, education policy, or industry. Sampling followed the logic of expert interviewing, i.e., interviewing participants with specific experience- and interpretation-based knowledge of the phenomenon (Bogner et al., 2014; Meuser & Nagel, 2009). This included professionals working with AI in their daily practice (especially industry experts) and participants from the other domains with substantial experience in pre- and in-service teacher education. To capture a broad range of perspectives on teachers' AI-related competence needs, diverse stakeholder groups were deliberately included, which were chosen based on prior studies (Brinda et al., 2025; Missomelius, 2016) to ensure coverage of key stakeholders. In total, 14 individuals were contacted, of whom seven declined due to time constraints. Thus, n = 7 German-speaking experts were interviewed (two from industry and one from each remaining domain). This distribution was chosen to compensate for the initially limited-time availability of industry experts by slightly oversampling this group. Although small in number, this sample reflects a deliberately broad and heterogeneous spectrum of relevant perspectives, which is essential for expert-based qualitative inquiry. The heterogeneity of the sample ensures that the interviews collectively address the conceptual domains identified in the scoping review and allows for a multi-faceted empirical elaboration of the competence model.

Data Collection

Semi-structured interviews were conducted by the author, an educational scientist with a focus on AI education and experience in qualitative research, via an online conferencing tool between March and May 2025. An interview guide (Mikula, 2026a) was developed based on the research questions without confronting the experts directly with Mikula's (2026c) model. Presenting predefined competence dimensions may have primed responses and would have increased the risk of confirmation bias. Instead, an open, experience-based elicitation was used to capture stakeholder-specific understandings of relevant AI-related competencies. Before conducting the n = 7 interviews, the interview guide was tested in two additional interviews, after which no changes were made. It covered relevant AI-related competence dimensions for teachers, their relations and structure, and positioning vis-à-vis existing competence models. At the beginning of each interview, the study objective was briefly restated, and afterwards, additional observations and participant information were documented. The interviews lasted 56 minutes on average. Interviews with industry experts were substantially shorter (approximately 38 minutes), as anticipated.

Data Analysis

All interviews were audio-recorded in compliance with the European General Data Protection Regulation, transcribed according to Kuckartz and Rädiker (2023), and anonymised. Data were analysed using structured qualitative content analysis to extract essential content (Kuckartz & Rädiker, 2023). Transcripts were imported into MAXQDA (MAXQDA Analytics Pro 24.11.0) and analysed iteratively through coding, review, and refinement. A deductive category system was first derived from the interview guide and applied to 15% of the data (n = 1 interview). Additional (sub-)categories were then developed inductively and discussed with other researchers to ensure argumentative validity (Krell & Lamnek, 2024). The remaining data were then coded, followed by a second discussion of the category system with additional researchers. After coding, reliability was assessed through intercoder checks and, two months later, intracoder checks using n = 2 randomly selected datasets (Wimmer & Dominick, 2014). For the recoding procedure, agreement at the segment level was considered satisfactory, and the coded segments were therefore regarded as identical when coders reached ≥ 90% overlap in the coded text segment (Kuckartz & Rädiker, 2023). Intercoder reliability was tested by an independent researcher using the coding manual (Mikula, 2026b). The proportion of identically coded segments with an overlap of ≥ 90% reached .83, corresponding to Cohen's $\kappa = .82$ (Kuckartz & Rädiker, 2023). For the intracoder test, conducted by the original coder, the percent of identically coded segments with an overlap of ≥ 90% was .82 and Cohen's $\kappa = .81$ (Kuckartz & Rädiker, 2023), indicating near-perfect reliability (Landis & Koch, 1977).

Ethics Statements

All participants provided informed consent for recording, anonymised analysis, use, and publication of their data for research purposes and were informed in writing beforehand. The study involved only adults, addressed no sensitive topics, and included no vulnerable groups. As all data were anonymised, formal ethical approval was deemed unnecessary. Nevertheless, the study adhered to established ethical standards for qualitative research and the European Code of Conduct for Research Integrity to ensure transparency, confidentiality, and consent (ALLEA, 2023).

Results

Based on structured qualitative content analysis, the material was coded into six main categories (Mikula, 2026b): competences, interrelations among competence domains, context-dependent differences in AI-related competences, competence measurement, positioning vis-à-vis other competence models, and teacher education. These were differentiated into 14 subcategories, partly with additional sublevels.

Competences

This category aggregates statements on specific competences teachers require in relation to AI. It comprises general AI knowledge, disciplinary knowledge, professional teaching competences, and personal and social dispositions.

General AI Competences:

This most frequently coded subcategory captures knowledge about AI functioning, limitations, risks, societal implications, and AI use that is considered relevant across subjects. It includes the subcategories technical–conceptual knowledge, socio-ethical perspective, and application competence.

Technical-Conceptual Knowledge: This subcategory includes knowledge about AI principles and technical backgrounds that teachers need, irrespective of subject. Participants emphasised that teachers require “a basic understanding of AI methods and concepts” (TN04), including “what AI models exist” (TN02), “what feeds the AI” (TN06), and “how […] we get from input to output […] and what role the textual basis plays in which this is computed” (TN02). Importantly, this is not meant as algorithmic expertise but rather “to show this technical part” (TN03) “without going into the algorithms” (TN03). Teachers should have at least “heard certain terms and be able to assess them” (TN02), not to develop comprehensive AI expertise, but to avoid “inadmissible expectations” or misconceptions about what AI systems can do (TN04).

Socio-Ethical Perspective: Participants stressed that, beyond technical knowledge, teachers require an understanding of AI limits, risks, and societal implications. Key aspects include “the consequences of a filter bubble” (TN01) or “what is real information, what is false information” (TN05). Participants also emphasised the need to understand structural and interest-related dimensions, such as “who are the providers and which goals do they have” (TN02), and data protection issues, including “which data may I provide to an AI system” (TN03). Further relevant issues were ethical dimensions and boundary questions, such as “ethical component[s]” (TN07) and “what AI can answer and what it cannot” (TN06).

Application Competence: This highly coded subcategory captures practical skills required for working with AI applications. It includes operational and usage competence, legal–ethical use, and reflective and evaluative competence.

Operational and usage competence refers to the ability to “master the tool [AI]” (TN06) and covers concrete use cases, including knowing “how one can interact with a machine” (TN07), i.e., through “formulating prompts” (TN03). It also includes using AI “particularly for lesson design” (TN07) or “as a meaningful didactic instrument in class” (TN04), as well as leveraging AI to “facilitate lesson organisation” (TN01). At the same time, some participants noted that the application perspective is important (TN04) but currently receives “almost too much focus” (TN04).

Legal–ethical use concerns responsible and legally compliant AI deployment, including using AI “in compliance with data protection” (TN01), ensuring “legal certainty in the use of tools” (TN03), and addressing ethical issues such as inclusion (e.g., when “children […] maybe speak other languages,” TN02) and the obligation “to ensure equal opportunities” (TN04).

Reflective and evaluative competence involves “critical reflection and critical questioning” (TN07) of AI-generated content, processes, outcomes, and the tools themselves, including “quality assurance, i.e., how do I verify an outcome” (TN06), judging “whether [something] was produced with GenAI” (TN04), dealing with bias, and “recognising […] the data basis” (TN03). It further includes assessing which tool can “perform certain tasks” (TN02) and reflecting on one’s own professional AI use, such as “from which perspective one is interacting with the model” (TN07) and when AI should be used or “consciously not used” (TN05).

Disciplinary Knowledge:

This subcategory comprises statements on teachers’ subject-matter expertise, such as “the ability to […] formulate a structured written text” (TN06) and “knowing how this works without the machine” (TN06). This disciplinary foundation was described as a prerequisite for further competence development, as teachers can “only use these tools sensibly if [they] have very solid generalist breadth knowledge” (TN05). Accordingly, participants stressed the need for teachers to have “high disciplinary competence” (TN01).

In addition, disciplinary knowledge includes AI-specific content knowledge, where AI itself becomes subject matter or a learning object. This concerns where and how AI should be addressed across subjects, with AI being in “computer science classes […] of course in the curriculum (TN03), while in “language subjects, AI becomes a learning topic, i.e., by examining “how it creates texts” (TN02). At the same time, participants emphasised that “it is not about AI being the learning object now” (TN02), rather, AI becomes a learning object through its use as a tool.

Professional Teaching Competences:

Those comprise the knowledge and skills required to plan, implement, and reflect on teaching and learning processes. They include pedagogical, subject-didactic, and AI-related didactic dimensions and thus represent core elements of teachers’ professional practice in educational contexts.

Pedagogy: Regarding pedagogy, participants referred to foundational pedagogical attitudes and competences that support AI use, including helping students “in their development, personality formation, self-efficacy, [and] motivational regulation” (TN04), teachers’ “ability to inspire” (TN01), and creating “a relationship between students and teachers” (TN06). Further aspects included “classroom management” (TN03) and fostering students’ “critical thinking” (TN01).

***Subject-Specific Didactics*:** Statements in this subcategory addressed the didactic logic of a subject and the ability to convey content in a learner-appropriate, structured, and effective way. Subject-specific didactics link disciplinary knowledge with classroom practice, including learning formats and tool use as well as teaching and learning about subject matter, but do not cover didactic aspects of using or thematising AI.

Teaching formats and the use of tools encompass methodological and media-related considerations such as "how we want to learn at school" (TN02), learning designs like "cooperative learning" (TN02), "which form of learning […] one wants to address" (TN07), and issues of "differentiation [and] autonomy" (TN02). It also includes "the question of how media and digital topics enter subject teaching" (TN05), requiring that teachers "clearly weigh where the added value is compared to alternatives" (TN03).

The domain of teaching and learning about subject content concerns preparing and "appropriately conveying" (TN04) disciplinary concepts so that learners can understand, apply, and deepen them. This includes "subject-specific didactic questions, i.e., what do I actually want my students to learn" (TN02), adapting instruction "to the respective target group" (TN07), and explaining "the content in different ways" (TN04).

AI Didactic: This subcategory addresses how teaching and learning with and about AI can succeed. Participants stressed that it "differs from general subject didactics [and] cannot simply be adopted" (TN02) from existing approaches. It includes the purposeful use of AI in subject teaching, and teaching AI-related knowledge and skills, assessing the competences developed as well as didactic framing and structural questions.

Those broader didactic framing and structural questions include institutional responsibility and boundary-setting, such as "do you want to allow AI" (TN05), "where is the limit of use, what must I document" (TN03), and issues of "assessment fairness [and] independence" (TN02). Participants also pointed out "how teaching and the exam situation have to change in view of AI and may then require a different setting" (TN01), as well as questions of "educational equity" (TN02) because tool quality differs and availability can depend on parents' background.

Statements on teaching and learning about AI focus on fostering knowledge, understanding, and reflection about AI systems as educational content. This includes ensuring learners "have an idea of how AI works" (TN02), covering "prompting" (TN03), "developing expectations […] about what I can expect from the system" (TN02), but "also to mindfully navigate the digital space and usage of information" (TN05). It further includes "ethical reflection" (TN04) and „giving students analytical ability" (TN01) while presenting content that is "technically correct but didactically appropriately reduced" (TN04). This aspect was often mentioned only after follow-up questions, as it "stands […] above teacher education" (TN06) but is nevertheless "extremely important for teachers" (TN02).

The most frequently coded aspect, teaching and learning with AI, in the subcategory AI didactics describes the didactically reflected use of AI systems in classrooms and learning processes. Teachers "think […] very deliberately about when to use what" (TN03) and design and accompany learning processes in which AI is used as a tool or "as a tutor" (TN03), i.e., via "chatbots that […] can answer individual questions quite well" (TN01). AI can also be used for lesson preparation, e.g., for the "creation of listening comprehension tasks" (TN03). The category further includes the learner perspective, where students use AI to support learning (e.g., practice or self-checking) and need clarification that learning "is not necessarily achieved if we simply copy and paste something" (TN02).

Personal and Social Dispositions:

This subcategory comprises statements on social skills, attitudes towards AI, professional development, and AI-related willingness, motivation, and volition. The subdomain social skills and abilities covers personal and interpersonal competences that are central for professional collaboration in schools and for building learning-supportive relationships beyond AI. This includes communication "with other colleagues […] the school leadership and […] parents" (TN01), "empathy" (TN06), and the ability "to establish a positive error culture and […] rethink traditional role understandings" (TN07).

Regarding attitudes towards AI, participants highlighted that teachers should avoid a dismissive stance, stressing the need "to drop this attitude of 'I don't need any of this' [, because] such an attitude is conveyed, and also passed on to students" (TN01). At the same time, "trust in this technology […], [that] everything works well and somehow has meaning and purpose" (TN03) was also viewed critically. Rather, teachers should "take a critical perspective so as not to believe everything that comes out" (TN07).

The aspect willingness, motivation, and volition captures dispositions essential for AI use and further qualification, including "saying you will work your way into it, but then also integrate it into your everyday work" (TN01), "a willingness to try things out yourself" (TN02), and "a willingness to acknowledge that others have different perspectives on the issue" (TN02).

Interrelations among Competence Domains

Participants frequently described the interrelations between competence domains as very strong, as "it builds on each other, […] it is all one package and in the end you cannot […] separate one from the other" (TN06). In particular, they emphasised the link between technical–conceptual knowledge, application competence, and the other domains, since teachers can "only use a tool confidently if [they] also know a little bit what is going on under the hood" (TN04). This, in turn, is supported by "good didactic concepts of how I convey it" (TN04), which also requires strong disciplinary knowledge, i.e., "knowing how this actually works without the machine in order to use the machine correctly" (TN06). Personal and social dispositions, such as attitudes, motivation, and willingness, were likewise seen as closely connected to all other domains, as they "determine every form of lesson design" (TN02). Engaging with AI was described as "a question of attitude […] and mindset" (TN02), because "if I completely refuse it, then I […] will not build any competence" (TN01).

Context-Dependent Differences in AI-Related Competences

This category captures statements indicating how requirements and emphases of AI-related competences vary by subject, school type, and grade level. Regarding differences between subjects, participants noted that AI-related competence needs may take different forms depending on the subject taught. At the same time, they stressed that “they all need the basic competence” (TN05) and that there should be “no differences, because it is relevant for everyone” (TN07), meaning that “a basic methodological competence [should] be taught to everyone, whether STEM or humanities” (TN04). However, this shared foundation requires “subject-specific manifestations” (TN02) during teaching, i.e., “technical tasks in mathematics and computer science” (TN02) were emphasised more strongly, whereas in other subjects, socio-ethical perspectives should receive greater attention. Importantly, this should “not be outsourced [to other subjects] but rather […] has to interlock” (TN01).

Similar considerations applied to differences between school types. Again, all teachers “need a basic level” (TN05). Beyond that, participants suggested that in grammar schools “slightly higher demands can be placed on the underlying mathematics […] but thematically […] very similar topics” (TN04) should be addressed across school types in secondary education, albeit at “different levels of abstraction” (TN01).

Finally, differences across grade levels were mainly described in terms of balancing an introduction to use with a deeper understanding. In early phases, teachers should create a “protected space” (TN02) in which AI systems can be used. In secondary education, students should then gradually build “these basic competences, this willingness, the technical skills, but above all also the ethical dimensions, opportunities and risks alike” (TN01).

Competence Measurement

This category comprises statements on whether, how, and under which conditions teachers’ AI-related competences should be assessed. Overall, participants considered it “useful to measure competences, because otherwise it remains […] vague and non-binding” (TN01). However, broad competence assessment was seen as premature, as teachers currently use AI only “sporadically” (TN03). Instead, assessment should be embedded in professional development activities, since teachers would otherwise likely be “not willing […] to take such tests” (TN02). Participants were also critical of existing instruments, stating that “current AI literacy tests […] convince zero” (TN04), because “multiple choice is […] hardly predictive of an actual understanding of the concepts” (TN04). Rather, assessments should be “both qualitative and quantitative” (TN07). Attitudes could be measured “via questionnaires” (TN02), whereas other domains should be assessed “via competence tests” (TN02), i.e., by eliciting “lesson planning, a lesson sketch” (TN02). A limitation noted was that such tests “depend on the curriculum and […] probably do not work universally” (TN04).

Positioning vis-à-vis other Competence Models

To situate the proposed model, this category captures how experts viewed other competence models, including general considerations, references to existing models, critiques, and perspectives on integration or extension. Overall, developing a competence model was considered useful "because those offer us a certain form of orientation" (TN07). One aspect discussed was that a competence model should be conceived "like a network" (TN02), with the output at the centre. Specific competences may relate to multiple domains, yet require "clear assignability" (TN02). Participants further argued for "linking competence models with didactic models" (TN07) to also address "how something can be taught" (TN07). Since "a model tries […] to abstract and […] reduce complexity" (TN02), it was seen as important not to lose the individual level through such "classification dynamics" (TN07).

Regarding specific references, it was notable that, particularly in the area of AI-related competences, no dedicated competence model was named even when prompted. Instead, participants referred to broader models such as the "Dagstuhl triangle for education in the digital world" (TN04), "Bloom's taxonomy" (TN04), "Baacke's media competence model" (TN07), or "Reinmann's didactic triangle" (TN07), as well as models developed "from practice" (TN02).

Models from practice were criticised as neither "educationally grounded nor strongly grounded in subject didactics" (TN02). More generally, models such as the "Dagstuhl triangle were said to indicate what but not how" (TN04) to teach, meaning that didactics "is missing in very many models" (TN04). Participants also noted that many models "do not necessarily provide good orientation for prospective teachers regarding which competences they need to foster and rather overwhelm them" (TN07), given the large number of aspects such as "this differentiation, these individual competences" (TN07).

Views on integrating AI into existing models versus developing an AI-specific model were mixed. On the one hand, AI was described as a "catalyst of digital transformation" (TN01) and should therefore be considered jointly, and it was seen as "useful to build on [a model] that has already been evaluated and validated" (TN02). On the other hand, participants argued that AI and digital literacy models should "remain separate for the moment" (TN03), emphasising that "AI is something specifically different from digitalisation" (TN02).

Teacher Education

For the targeted development of AI-related competences, participants considered it crucial at which phase of teacher education the acquisition takes place. The interviews referred to the three phases of teacher education in Germany: university studies, the preparatory service (Referendariat), and in-service professional development.

The interviews clearly emphasised that "during the course of study, [the content] can be much more abstract [...], technical [and] theoretical" (TN02). And that "the basics […], i.e., how AI works" (TN06) should be taught. At the same time, participants stressed that such content should be didactically connected and structurally anchored, as AI constitutes a "cross-cutting task that keeps recurring" (TN01).

In the second phase, the preparatory service (Referendariat) should focus primarily on "didactics and pedagogy" (TN04). In addition, the "use of AI tools should be practised at the latest during the preparatory service" (TN03), that is, "testing things and then focus on the learners" (TN02), while application should "build on [the prior knowledge] from university studies" (TN06).

For in-service professional development, participants highlighted both "networking […] within subject departments" (TN03) and training "at the academy for teacher professional development" (TN01) as key settings in which teachers can be trained "as multipliers" (TN02). It was also noted that teachers can "further educate themselves via online resources" (TN02) or receive "monthly updates via newsletter on the latest developments" (TN06). Professional development content should focus "more on situations" (TN01), "concrete applications […], showing examples of what works well" (TN03), and, more broadly, "new topics and aspects in the subject" (TN04).

Discussion

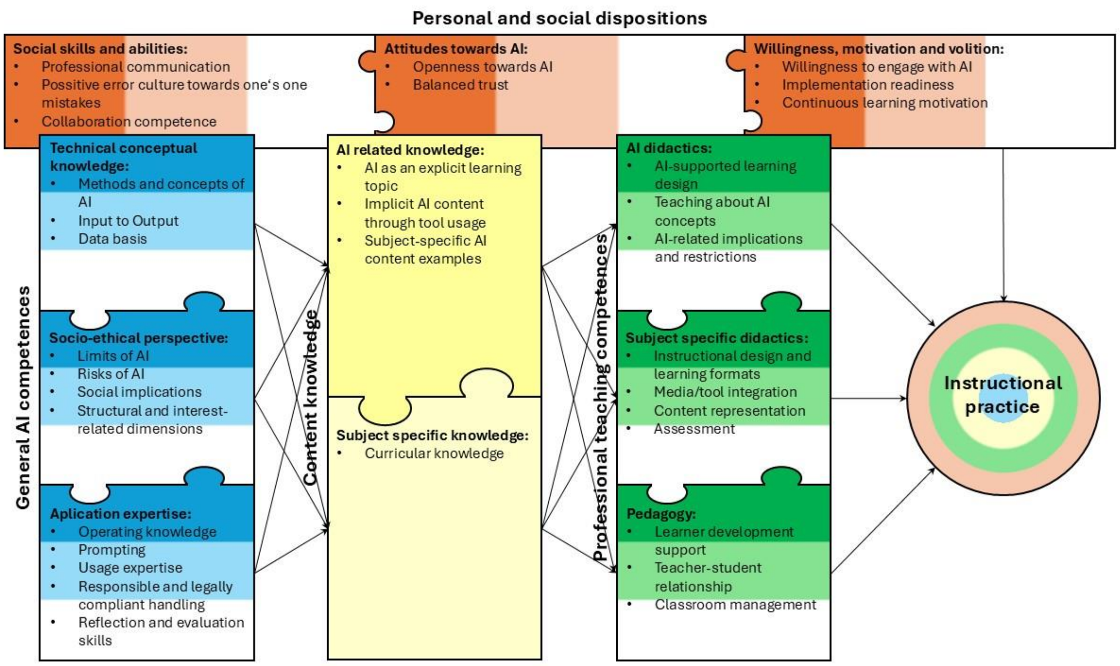
The discussion places the interview findings in the context of the previously proposed competence model (Mikula, 2026c), identifying which assumptions were confirmed and which dimensions require refinement, answering RQ1 and RQ2. It also highlights areas where the data indicate new conceptual needs. Furthermore, the methodological approach is critically reflected upon, limitations are identified, and an outlook on implications and future research is provided.

Regarding RQ1, the findings highlight the diversity of AI-related competences teachers need to deliver successful instruction. The qualitative analysis largely supports the theoretically derived results of Mikula's (2026c) scoping review and further differentiates them, particularly in the areas of professional teaching competences and personal and social dispositions, which is also informative for RQ2.

The interviews provide strong support for the core assumption of the model that instructionally relevant AI knowledge forms the basis of AI-related competences for teachers (Mikula, 2026c). Although the experts stressed that algorithmic depth is not required, they simultaneously highlighted the necessity of a basic understanding to prevent misconceptions and uncritical trust in AI systems. This tension reflects the ongoing debate in the field between overly technical approaches and those that remain too superficial (Mikladze, 2024; Shiri, 2024). Notably, the experts emphasised socio-ethical aspects, such as recognising bias, assessing reliability, and understanding data practices more strongly than expected. This suggests that general AI knowledge is perceived less as technical expertise on how AI systems work alone, reinforcing the idea that this dimension comprises three closely linked sub-components: technical-conceptual knowledge, socio-ethical perspectives, and reflective application expertise, and thus supports the classification of the Dagstuhl and Frankfurt Triangle (Brinda et al., 2025; Missomelius, 2016; Weich, 2019). Consequently, as the interviews indicate, the focus shifts away from a predominantly technical perspective toward a more practice-oriented and pedagogically grounded approach, as shown in Figure 2 of the empirically refined model.

Figure 2

AI-related competences for teachers



A further implication of the findings is that subject-specific content remains a prerequisite for any good instructional practice. At the same time, the findings indicate that AI-specific content has not yet been firmly established in practice as an independent component of subject education. One possible explanation is that AI remains a relatively new field for many teachers and, outside computer science, is rarely explicitly anchored in curricula (Rieck & Hellmig, 2025). This is also indicated by the fact that teaching about AI is predominantly marginalised or only implicitly included in existing competence models (Mikula, 2026c) and therefore rarely considered in terms of where and when AI content becomes part of the subject content. Consequently, the development of AI-specific knowledge requires more than theoretical definition, it needs clearer curricular anchoring and subject-specific examples that illustrate where AI intersects with disciplinary logics (Elstad & Eriksen, 2026). For the further development of the competence model, this thus implies that the content knowledge dimension (Figure 2) should be understood as a highly subject-dependent structure in which subject knowledge is a prerequisite for classifying AI content, reflecting on it, and, if appropriate, treating it as a learning object.

A significant contribution of the study is the backing and refinement of the AI didactics dimension. While the theoretical model had already distinguished this domain (Figure 1), the interview data reveal its practical relevance more clearly than anticipated. The experts stress that AI didactics concerns not only teaching and learning with AI, but, crucially, teaching and learning about AI. Notably, participants mentioned this aspect only after explicit prompting, suggesting that teaching as such is often perceived as a well-established, general competence of teachers that does not require explicit mention, and may therefore be underrepresented in existing models, such as Intelligent-TPACK (Celik, 2023) or Delcker et al.'s (2025) model. The findings demonstrate that AI didactics involves both novel AI-specific demands, such as new learning arrangements, assessment formats, or preparation processes, and the instructional requirement to teach about AI, including ethical, societal, and conceptual aspects. At the same time, subject-specific didactics remains essential for structuring content, designing tasks, and aligning learning processes with disciplinary logics, while being closely intertwined with broader pedagogical practices such as supporting students, fostering motivation, and building productive learning relationships, according to the experts. Together, these elements form the pedagogical-didactic foundation on which teachers build effective learning processes, including those involving AI. Overall, the results substantiate the need to conceptualise AI-didactics as an independent subdimension alongside subject-specific didactics and pedagogy (Figure 2), as it captures instructional challenges introduced by AI that current didactic structures neither anticipate nor sufficiently address (Mikula, 2026c).

The findings refine the role of personal and social dispositions by showing that they operate less as a complementary dimension and more as an enabling condition for all other areas. It is noticeable that aspects such as empathy, communication skills, and the creation of a positive culture of error are described as professional fundamentals whose importance is further heightened by AI. Similarly, the central demand regarding attitudes towards AI was less an increase in competence than the ability to adopt a reflective professional position between refusal and uncritical use. This indicates that limited AI-related competence is not only a function of knowledge gaps but also depends on whether and to what extent teachers are prepared to engage with AI as a new field, use AI, and develop professionally on an ongoing basis. In this sense, personal and social dispositions are not an additional competence domain but an enabling frame within which AI-related competences become actionable.

Although minor differences emerged across subjects, school types, and grade levels, these variations appear to concern the emphasis and depth of AI-related competences rather than their underlying structure. This supports the original model's assumption that AI constitutes a cross-curricular professional requirement for all teachers and that the competence dimensions should incorporate different proficiency levels (Mikula, 2026c), which can also be found in similar models (Ng et al., 2021; Redecker, 2019; UNESCO, 2024). Hence, the observed differences point primarily to the need for subject-sensitive operationalisation rather than subject-specific structural models. At the same time, the findings indicate that clearer curricular guidance is required to translate general competences into subject-specific learning opportunities, particularly regarding content knowledge. Overall, the results support the notion of a shared core of competences that can be adapted according to the subject context.

Furthermore, participants suggested that standardised assessment is currently only partly appropriate. Test- and task-based approaches were seen as suitable for cognitive and didactic aspects, whereas personal and social dispositions were better captured via self-assessment. Criticism targeted overly reductive formats, particularly knowledge-only or multiple-choice instruments that fail to reflect the complexity of AI-related competence requirements. Overall, a combination of performance-based assessment and self-report measures appears appropriate across teacher education according to the experts. Concerning positioning vis-à-vis other competence models, experts reiterated their orienting function for teacher education. Notably, even when prompted, they could hardly name dedicated AI-related competence models and instead referred mainly to broader models from media or digital education. This suggests that no AI-related competence model has yet been established in professional discourse, reinforcing the need to systematise AI-specific requirements while remaining connected to educational science and subject-didactic traditions. Building on these and the above-mentioned insights, the refined model offers a more coherent and detailed structure by integrating all necessary dimensions and a clearly delineated AI-didactics dimension (Figure 2). It therefore not only extends existing frameworks but fills an empirically substantiated conceptual gap that current approaches neither anticipate nor systematically address.

Methodical Reflection, Limitations, and Conclusion

The methodological reflection in this study was based on the quality criteria for qualitative content analysis according to Kuckartz and Rädiker (2023). Internal study quality was supported through the deductive–inductive coding strategy, the coding manual (Mikula, 2026b), and the systematic rule-based application of categories to the material. Intersubjective traceability and auditability were ensured via detailed documentation of data collection, analysis procedures, and software-assisted analysis. Coding reliability was established through inter- and intracoder checks. Credibility was strengthened by closely linking interpretations to the data and by presenting key findings in a text-near manner. Concerning external study quality, the category system, coding manual, and results were discussed with other researchers for argumentative validation (Krell & Lamnek, 2024).

Despite these measures, several limitations should be noted. They mainly relate to the data collection format and the sample. As the study employed expert interviews, the sample reflects a deliberately heterogeneous but necessarily small group of specialists. In qualitative expert research, such sample sizes are appropriate for capturing domain-specific reasoning, yet they do not allow conclusions about the prevalence of particular perspectives. Future studies could therefore extend the empirical basis by including larger samples of pre-service and in-service teachers or by combining qualitative insights with survey-based operationalisations of the competence dimensions. Moreover, the interviews were conducted, coded, and interpreted in German, while selected quotations were translated into English for reporting. Although care was taken to preserve meaning through context-sensitive translation, minor shifts in nuance or tone cannot be fully excluded when rendering participants' original wording. The study was conducted in a dynamic field, meaning the findings should be interpreted as a snapshot at the time of the interviews. Finally, as the author conducted all stages of the study from the theoretical basis to data collection, coding, and analysis, the researcher's influence cannot be fully excluded. To ensure analytic transparency, the coding process followed a rule-guided procedure supported by a detailed coding manual, iterative discussions of category definitions, and reliability checks, thereby providing argumentative validation of the interpretive steps.

Nevertheless, this study provides an empirically grounded refinement of a competence model for teachers' AI-related competences by integrating perspectives from diverse stakeholder groups. While a detailed comparative analysis of existing frameworks was conducted in the underlying scoping review (Mikula, 2026c), the present study complements this work by providing empirical insights into how these competence dimensions are perceived, prioritised, and interrelated from different stakeholder perspectives. In particular, they demonstrate that AI-related competences for teachers extend beyond technical knowledge and tool use and must be understood as a multidimensional construct that integrates disciplinary knowledge, pedagogical and didactic competences, and enabling personal and social dispositions.

A central contribution of the study lies in highlighting the pivotal role of AI didactics as a distinct and indispensable dimension of teachers' AI-related professional competences. The results show that effective teaching with and about AI not only requires the purposeful integration of AI tools into learning processes but also the ability to address AI as a subject of learning, including its technical foundations, limitations, and ethical implications. In this sense, AI didactics emerges as a key interface between general AI knowledge, subject-specific teaching, and pedagogical practice.

Furthermore, the findings emphasise the strong interrelatedness of all competence domains and the enabling function of personal and social dispositions, which shape whether and how teachers engage with AI in their professional practice. Overall, the study contributes to the systematisation of AI-related competence requirements by providing an empirically informed and didactically actionable framework that can support both research and the development of teacher education.

Building on the empirical findings, several implications for future research and teacher education can be derived. First, the results highlight the need to conceptualise and further elaborate AI didactics as an independent competence dimension. While this study provides initial empirical support and differentiation, the dimension requires more fine-grained theoretical and empirical specification. In particular, future work should aim at a clearer operationalisation of its internal structure, ensuring that all three core subdomains are systematically and equally addressed. This is especially relevant for initial and continuing teacher education, where AI didactics should be integrated as a distinct focus area rather than being treated as a marginal extension of existing pedagogical or subject-didactic approaches.
Second, the empirical basis could be further expanded by including additional stakeholder groups. While this study incorporated expert perspectives from multiple domains, future research could systematically include pre-service teachers as a key group. Their perspectives are crucial for understanding how AI-related competences are perceived, acquired, and enacted in the different phases of teacher education, and for aligning competence models with actual learning needs and professional development trajectories.

Finally, the findings point to the importance of translating the proposed competence model into practical formats for teacher education. One promising avenue is the development and implementation of seminar-based learning environments for pre-service teachers, in which the different competence dimensions are explicitly addressed. This would also allow for iterative refinement and validation of the model in authentic educational settings.

Overall, future work should aim to further operationalise, empirically validate, and practically implement the proposed competence framework in order to support teachers in effectively and responsibly shaping teaching and learning with and about AI.

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Declarations

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