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Developing a holistic AI literacy assessment matrix – Bridging generic, domain-specific, and ethical competencies

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ABSTRACT

Motivated by a holistic understanding of AI literacy, this work presents an interdisciplinary effort to make AI literacy measurable in a comprehensive way, considering generic and domain-specific AI literacy as well as AI ethics. While many AI literacy assessment tools have been developed in the last 2-3 years, mostly in the form of self-assessment scales and less frequently as knowledge-based assessments, previous approaches only accounted for one specific area of a comprehensive understanding of AI competence, namely cognitive aspects within generic AI literacy. Considering the demand for AI literacy development for different professional domains and reflecting on the concept of competence in a way that goes beyond mere cognitive aspects of conceptual knowledge, there is an urgent need for assessment methods that capture domain-specific AI literacy on each of the three competence dimensions of cognition, behavior, and attitude. In addition, competencies for AI ethics are becoming more apparent, which further calls for a comprehensive assessment of AI literacy for this very matter. This conceptual paper aims to provide a foundation upon which future AI literacy assessment instruments can be built and provides insights into what a framework for item development might look like that addresses both generic and domain-specific aspects of AI literacy as well as AI ethics literacy, and measures more than just knowledge-related aspects based on a holistic approach.

1. Introduction

Research on artificial intelligence (AI) literacy and AI education is critical in today's technology-driven world. Given the ubiquity of AI-based technologies in professional work environments and the harm they can cause when poorly designed or applied, there is an urgent need for individuals to have the competencies that will enable them to confidently use and assess the consequences of AI technologies in professional workflows. AI literacy, as defined by Long and Magerko [107] or Faruqe et al. [54], encompasses a broad, general set of knowledge and skills or competencies required by individuals interacting with AI technologies. This concept goes beyond mere familiarity with AI; it addresses how these competencies vary across domains and disciplines. In this regard, a holistic understanding of AI literacy exceeds generic AI literacy and focuses additionally on domain-specific and interdisciplinary AI competencies tailored to the needs and applications within specific professional domains. However, prominent AI literacy frameworks often overlook the nuances of domain-specific differences and do not align along more holistic competence dimensions, like those of cognition, behavior, and attitude, which are all necessary for real-world competence deployment [32,176,182,185]. Furthermore, they do not provide clear guidance on how to effectively operationalize these diverse aspects when it comes to assessing AI literacy. This conceptual research paper addresses these gaps and aims for a holistic approach to AI literacy measurement by introducing a framework that distinguishes between generic AI literacy, domain-specific AI literacy, and their unique contextual factors, and explicitly addresses AI ethics as being center stage for AI competencies. It also delineates cognition, behavior,

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and attitudes in AI literacy [13,121,129,168,176], and explores appropriate measurement and operationalization approaches.

This paper is divided into six sections. First, it briefly introduces the concept of AI literacy, considering its origins and its relationship to earlier literacy terminologies, such as digital literacy [46,62] or statistical literacy [59]. Second, it discusses AI literacy as a generic competency, delineating the aspects of AI literacy that each individual will need to thrive in an AI-infused world. Third, in contrast to generic AI literacy, the importance of domain-specific AI literacy will be explained, taking into account contextual factors such as specific roles or tools that shape the daily work routine in each professional domain. These two aspects will be enriched by AI ethics literacy as another general-purpose competency that deserves its own attention and shall not be subsumed under either generic or domain-specific AI literacy. Fourth, to open our AI literacy framework, we will outline the notion of competence (or literacy) along the dimensions of cognition, behavior, and attitude, considering different approaches to operationalize these aspects. Fifth, following this theoretical background, we will then present a holistic AI literacy assessment matrix to exemplify the utility of our framework (e.g. for guiding operationalization and future development of instruments for different areas of application), which will be thoroughly explained and explored through three professional domain use cases: AI literacy for medicine, AI literacy for education, and AI literacy for engineering. Finally, we will reflect on and discuss the usability of our provided AI literacy assessment matrix for future guidance on scale developments and AI educational alignments, as well as provide an outlook on future research perspectives.

2. Related work

2.1. AI literacy – existing constructs and frameworks

While AI's integration into our daily surroundings is not a recent phenomenon, given that numerous user-oriented technologies and applications already employ machine learning algorithms, the permeation of AI technologies into our societies, workplaces, and personal lives is becoming more pronounced [70,165]. This calls for specific AI-related competencies, i.e. AI literacy, that will allow one to grow and act with sovereignty in this new era. The recent emergence of generative AI technologies, with large language models such as GPT-4 or Google Gemini, as well as emerging reports on harms related to the use and design of AI technologies [40], highlight an even more pressing relevance in the encounter with educational efforts and related assessment tools for AI literacy [33,35]. With this increasing pervasiveness of AI in our decision-making processes and daily routines, there is, paradoxically, still a lack of awareness among people about the extent of AI use, its inner workings, and its potential impact on their lives [60,180]. Similar to how digital literacy [62] has empowered individuals to use digital information and communication technologies, learning to become AI literate is increasingly critical to interacting with the AI systems that are ubiquitous in our personal and professional surroundings [127,162].

The concept of AI literacy was first discussed by Kandlhofer, Steinbauer, Hirschmugl-Gaisch, and Huber [87], and then significantly shaped in a widely cited paper by Long and Magerko [107]. Here, the authors define AI literacy as "a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace" ([107], p. 2). There are different views on what exactly AI literacy is and what skills AI-literate people should have [98]. However, there is a strong consensus that AI literacy is primarily for non-experts, people who are not directly involved with AI through their studies or work and who have not received formal training in AI [98,127,135]. This very fundamentality of AI literacy for society was also described by Kandlhofer et al. [87], where they introduced literacy in AI by analogy to classical literacy such as reading or writing. To participate within this AI-infused world as an informed and responsible person, it is the general population and every digital citizen to whom our AI education efforts should be tailored, as it is foreseeable that AI literacy will become a key competency for work, everyday life, and lifelong learning [107,127,171], similar to digital [46,62,160], information [86,104], or basic computer literacy [57,154] in the past.

Internationally, researchers are urging the need to promote AI literacy and generate greater interest in the subject among the general public [31,87,108,145]. Following this call, several international policies and educational frameworks targeting AI education have been published, or existing frameworks have been complemented with AI literacy considerations. One of the most prominent examples in this area is the DigComp, the European Union's Digital Competence Framework for Citizens [171]. This framework includes key digital competencies in the areas of information and data literacy, communication and collaboration, digital content creation, safety, and problem solving. In its current iteration, DigComp 2.2 [171], these competencies are comprehensively described along eight proficiency levels, as well as illustrative examples of each of these competencies (including their sub-aspects) along the dimensions of knowledge, skills, and attitudes.

Of particular relevance to AI literacy research, DigComp 2.2 also includes a chapter on "Citizens interacting with AI systems". The authors write that "for citizens to engage confidently, critically, and safely with new and emerging technologies, including artificial intelligence (AI), they need to acquire a basic understanding of such tools and technologies" ([171], p. 77). This is also in line with the very fundamental call of international research, which urges the advancement of AI literacy not only for specific groups, but for society as a whole. Within DigComp 2.2, this is also justified by the fact that AI-related knowledge, skills and attitudes can serve as resources for several challenges, such as ethical issues, data protection and privacy, or bias in various forms. It therefore emphasizes the importance of citizens interacting with AI systems, rather than focusing on AI knowledge alone. To shape this approach within this educational framework, they explained five central themes and topics that citizens should learn, namely: 1. What do AI systems do and what do they not do; 2. How do AI systems work? (including awareness of what AI is); 3. When interacting with AI systems (...in terms of searching for information, using AI systems and apps, or focusing on privacy and personal data); 4. The challenges and ethics of AI; 5. Attitudes regarding human agency and control.

Another international policy framework has recently been developed by UNESCO, entitled "Guidance for generative AI in education and research", which also proposes several steps deemed necessary to foster an AI-competent society and to implement in particular generative AI technologies in educational institutions and contexts [80]. In addition to regulatory and legislative aspects, they also suggest the development of AI competencies, including Generative AI (GenAI) related skills for learners, as "the development of AI competencies among learners is key to the safe, ethical and meaningful use of AI in education and beyond" ([80], p. 25). In particular, "latest developments of GenAI have further reinforced the urgent need for everyone to achieve an appropriate level of literacy in both the human and technological dimensions of AI, understanding how it works in broad terms, as well as the specific impact of GenAI." ([80], p. 26).

Providing such frameworks in addition to current research on AI literacy is central to addressing the acute shortage of skilled workers in the field [5], while strengthening the ability to use AI confidently and responsibly across the board.

2.2. AI literacy assessment approaches

Providing AI learning opportunities alone, in the form of AI educational programs and courses, is not enough to promote the vision of an AI literate society. The design of educational content also depends on the availability of good AI literacy assessment tools, as a valid measurement of AI literacy is a necessary condition for evaluating the effectiveness of

AI literacy interventions in any educational setting, be it K-12, higher education, adult education, workforce development, or in the context of online learning.

Several assessment instruments already exist that measure certain aspects of AI literacy. The first validated self-assessment scale for AI literacy was developed and evaluated by Wang et al. [173]. Although questionnaires for surveying AI literacy existed prior to this scale, they were neither particularly content-valid nor psychometrically tested. Wang et al. [173] used exploratory and confirmatory factor analyses for model generation and model validation, and ultimately listed 12 items that can be used to self-assess AI literacy using Likert scales. Shortly after the publication of this first self-assessment scale, similar instruments were published that correspond to the core idea of the Wang et al. [173] scale. These include the scales by Carolus et al. [29], Pinski and Benlian [134], Laupichler et al. [97], Tully et al. [167], and Ng et al. [128]. However, all these instruments have in common that they rely exclusively on the self-assessment of the respondent. Yet, this may be subject to certain confounding factors (e.g., social desirability) and might therefore only be useful if taking the assessment is not associated with specific consequences for the respondent [49], such as promotion at work or being assessed in a university course. Particularly, in some situations, such as assessing the level of AI literacy in a population to decide on further measures to improve it, it is important to test AI literacy as objectively as possible. Weber et al. [175] and Hornberger et al. [81] have therefore developed AI knowledge measurement tools that *test* respondents' knowledge (rather than having them self-assess their knowledge). For this purpose, they used multiple-choice questions based largely on common AI literacy constructs (e.g., [107]) and measures from item response theory (IRT) to optimize the objectivity of their assessments. Taking this into perspective, the majority of the questions in the self-assessment scales and AI literacy tests deal solely with AI knowledge and AI skills, completely leaving out affective components such as "attitudes toward AI (ATAI)". Schepman and Rodway's GAAIS [149,150] and Sindermann et al.'s ATAI scale [157] are two of only a few examples of "attitudes toward AI" scales that have been systematically validated and used in various contexts. Other ATAI scales have been published by Suh and Ahn [163] and Grassini [64].

Additionally, for the realm of AI ethics, different measurement approaches can be named. To deal with the impractical measurement foundations of ethics, many researchers established their own measurements for each case. For non-professionals, Shih et al. [155] investigated the effects of their AI ethics course by measuring 15 items on 4 ethical principles (transparency, responsibility, justice, benefit). Jang et al. [84] created the AT-EAI 17-item scale for investigation of adherence to the five ethical dimensions of fairness, transparency, non-maleficence, privacy, and responsibility. Hess and Fore [77] highlight measurement approaches that go beyond philosophical ethics (self-assessment of awareness of, knowledge of, or solutions for ethical issues) such as extra-curricular involvement, problem-based service learning [183] or in-depth qualitative analysis through short texts or position papers [74]. Others focused on personality traits or multiple-choice answers for ethical scenarios to evaluate decision-making strategies as well as meta-cognitive reasoning strategies [92]. Another approach was reframing technical problems for multiple solutions leading to a need for moral reasoning [42].

Both the existing self-assessment instruments and the IRT-scaled test instruments currently still mostly represent a very broad and generic construct of AI literacy operationalized by its items. This seems to make sense for measuring AI literacy of non-experts, although some aspects, such as human-AI interaction skills and behavioral indicators, are largely neglected. However, the more specialized the measurement of AI literacy is to be for specific contexts and occupational groups, or the more specific educational contexts are to be examined, the more it becomes necessary to focus on professional demands-related aspects of AI literacy in addition to generic AI literacy [151]. In developing a holistic AI literacy measurement, we, therefore, follow several voices in the research community calling for the development of assessment tools that measure both domain-independent (generic) and domain-specific AI literacy, as well as ethical considerations, and conceptually consider not only knowledge aspects but also skills and attitudes [18,54,98,127,151]. Such instruments would help assess individuals' AI competencies in their professional field, while also allowing for the collection of data to validate the impact of AI literacy for specific professional contexts. The goal of this paper is to lay the groundwork for a refined and comprehensive approach to measuring AI literacy that considers this distinction between generic and domain-specific AI literacies and specifically considers AI ethics competencies.

3. Conceptual framework: towards a holistic AI literacy assessment matrix

The following sections outline the conceptual framework of our approach. This framework, consisting of generic AI literacy, domain-specific AI literacy, and AI ethics literacy, forms the basis for the holistic AI literacy assessment matrix that is prototypically presented in the conceptual framework section (see Table 1).

3.1. The horizontal dimension – AI literacy Types

3.1.1. Generic AI literacy

The notion of non-expert AI literacy explained above [97] forms the basis for a concept we call generic AI literacy, which describes AI-related competencies (cognitions, behaviors, attitudes) that every citizen should possess, regardless of their discipline or workplace role. Generic AI literacy is a basic understanding of AI and thus the ability, knowledge, and skills to understand, monitor, effectively interact with, and critically reflect on AI-based technologies for basic daily and work purposes in a way that allows citizens to participate and act with confidence in an AI-driven world [45,98,107,127]. Therefore, it can also be positioned as a context-independent key competency that is equivalent in its use and effectiveness across a wide range of different tasks, situations, and interactions involving AI, thus meeting the demands that many people face in everyday and social life in today's information society [107,176]. Generic AI literacy for non-experts is also characterized by not being involved in the construction and development of AI models per se, a domain that rather characterizes AI experts and professionals [97]. Rather, in accordance with other conceptualizations of generic skills, generic AI literacy encompasses cognitions, behaviors and attitudes that are not specific to any particular professional domain [3,4,105,123,190]. Following this, we also align our conceptualization of generic AI literacy with the five questions that Long & Magerko [107] suggest as the fundamentals of AI literacy: "What is AI?", "What can AI do?", "How does AI work?", "How should AI be used?", and "How do people perceive AI?". According to their framework, the development of generic AI literacy should equip users with the ability to answer these questions and enable them to understand the core principles of AI [34].

Generic AI literacy can also be positioned as a fundamental skill, similar to other essential skills for lifelong learning, such as digital literacy [10,30]. The notion of certain required literacies for dynamically

Table 1
Conceptual framework for the holistic AI literacy assessment matrix.

		AI literacy type		
		Generic	*Domain-specific*	*Ethics*
Competence dimension	*Knowledge/ Cognition*			
	Skills/ Behavior			
	Attitudes/ Values			

changing life and work environments has already proven its crucial importance, as much research has been done in the last two decades on digital literacy as a requirement for proactive interaction in a digitalized world [46,62,83,160,184]. While these skills are still very much needed, the current disruption and widespread availability of AI-based technologies requires that AI literacy is considered in every aspect of such digital literacies, representing a comprehensive 21st-century socio-technical competency [127,134]. The implication is to conceptualize AI literacy as another key competency that complements existing notions of digital literacy.

While digital literacy has been understood as preparation for the challenges of the digital information society, analogously AI literacy must be understood as preparation for a society permeated by artificial intelligence. Following this, generic AI literacy should encompass a broader set of competencies, including socio-emotional literacy [130], socio-cultural abilities [78], and other transferable skills such as communication and collaboration [12,128], fundamentally enabling AI non-experts to thrive and participate in an AI-infused world. Thinking methodologically, in the context of competence models and assessments, it is therefore necessary to consider which competencies must be available to all members of a social group, which in terms of AI literacy aims at enabling an AI-literate society, but also which competencies should be available in a complementary way, e.g. for the purposeful use and integration of AI technologies in specific professional domains [22, 127,176]. Accordingly, the following section introduces the concept of domain-specific AI literacy as specific AI competencies that are relevant to the purposeful and confident use of AI for professional endeavors.

3.1.2. Domain-specific AI literacy

Alongside generic AI literacy, there is an urgent need to integrate domain-specific AI literacy as a necessary component of a holistic and comprehensive approach to AI literacy when applied in practice within professional domains (e.g., medicine, education, engineering). Since generic AI literacy may not compensate for a lack of domain-specific AI literacy, a specific form of AI literacy may be necessary to address the needs of each domain [4,176]. Accordingly, the word "domain" refers to the specific field or discipline in which AI is implemented or used. Domain-specific AI literacy is underexplored in current research, but important insights could be gained from the literature dealing with the design of AI education [18,30,147,151]. These AI educational endeavors suggest that domain-specific AI literacy as a concept might refer to the capacity to integrate the knowledge of AI with the comprehension of its application requirements within a particular professional field.

Important research findings that necessitate a domain-specific view of AI literacy also result from the approaches of professions and expertise research, in which the understanding of domains is linked to different "fields of learning", i.e. life-world or professional fields of action or knowledge- and experience-based action routines as a component of expertise [51,52,67,191]. For example, Bromme [24,25] distinguishes domain-specific knowledge of expert teachers for different school subjects. Tricot and Sweller [166] argue for a domain-specific view of knowledge because intellectual abilities can be better explained by long-term memory and by the high performance of experts in certain domains, such as air traffic control or chess. In general, expertise research distinguishes between well-defined and poorly defined domains based on the characteristics of the challenges or problems to be solved [68]. Well-defined domains are characterized by clear problem statements, unambiguous solution methods, and defined success criteria. In contrast, poorly defined domains are characterized by complexity, ambiguity, and conflicting solution approaches.

In the area of domain-specific AI literacy, Schleiss et al. [151] provided a framework for the development of domain-specific AI education courses. The authors argue that the relevance of AI in various domains requires that the development of AI courses should be aligned with its domain, creating so-called domain-specific AI courses. Following this line of reasoning, domain-specific AI literacy focuses on the use of AI as a tool in professional or academic settings. This is increasingly important, as students outside of computer science often feel unprepared for the growing integration of AI into their fields [136,151,158]. This is accompanied by widespread misconceptions about AI and a limited understanding of AI's capabilities and limitations for one's professional domain or field of study [14]. One difficulty for domain-specific AI education and AI literacy may be that the applications of AI and the competencies required for each may vary widely across domains and disciplines, making different aspects of AI literacy differentially significant depending on the professional domain [50]. Another challenge is the emerging interdisciplinarity of domain-specific AI literacy, which considers the domain requirements for the application of AI in that domain and thus goes well beyond the concept of generic AI literacy, requiring that the constructors of domain-specific courses themselves possess both domain and AI knowledge [189]. Furthermore, the use cases, implications, and underlying data of AI technologies differ across domains [65,132], indicating that domain-specific AI literacy requires flexible adaptations that cannot necessarily be derived from other domain use cases. Taken together, these aspects may also explain the gap in domain-specific AI education courses identified by Schleiss et al. [151]. Nevertheless, although very demanding, this outlined context provides the boundary conditions under which domain-specific AI literacy comes into play and offers opportunities to take these very aspects into account when conceptualizing domain-specific AI literacy. In sum, domain-specific AI literacy can be described as the ability to bridge an understanding of AI with an understanding of the needs for its application within that specific professional domain.

When conceptualizing domain-specific AI literacy and related assessments, it may be tempting to think primarily about the use of specific tools. Although domain-specific AI education often aims to equip learners with knowledge about specific AI tools for their domain [144, 169,186], this pragmatic approach should be enriched with aspects of knowledge about specific data, the impact of AI use on the domain, and ethical issues, so that it does not get perceived as pure "*tool literacy*", as the sole ability to use certain AI tools, without considering its broader implications. In accordance with Schleiss et al.'s [151] planning framework for AI course design, we propose that domain-specific AI literacy should include and represent three distinct aspects: First, potential AI use cases ("What are the potential use cases for using AI in the domain?"). There the goal is to help identify existing applications and predict potential future scenarios where AI can contribute to solving problems within a specific domain. Second, the data in the domain ("What type of data is most common in the domain?" / "Is the data in the domain abundant or scarce?"). This aspect is crucial because understanding the common types of data within a particular domain facilitates the more precise application of AI methods and the definition of the data involved. The nature of the data – whether it is time series, text, images, or other forms of data – has a significant impact on the AI techniques that should be taught. And third, the implications of using AI in the domain ("What are the implications (ethical, legal, social) of using AI in the domain/use case?"), taking into account the possible consequences of using AI in a particular domain, especially in terms of ethical, legal, and social implications. Domain-specific AI literacy assessments should therefore reflect at least these three central themes in their item pool.

The gap in domain-specific AI education courses is also evident in the context of AI literacy assessments. While numerous AI literacy assessments have emerged in recent years, they mainly focus on generic AI literacy but do not meet the requirements for measuring AI literacy in specific domains. Accordingly, domain-specific AI literacy is included in our holistic AI literacy assessment matrix as an area that is still lacking in research but is of paramount importance if AI literacy is to be integrated into professional practice. For the development of domain-specific AI literacy assessments, it may be essential that adaptations of existing assessment instruments can be flexibly evolved. The use of generative AI may be fruitful for this purpose [99]. A first attempt to generate domain-specific items based on existing item structures is shown in our exemplary completion of the holistic AI literacy assessment matrix for the professional domains of medicine, education, and engineering (see Section 4).

Given the paramount importance of knowledge about the impact and consequences of AI use in general as well as within a domain, we decided that AI ethics should be a stand-alone dimension on the horizontal axis alongside generic and domain-specific AI literacy [20,39,113].

3.1.3. AI ethics literacy

The seamless integration of AI technologies into daily activities often goes unnoticed, impacting lives without explicit recognition [53]. The lack of transparency on the one side, but also the lack of understanding of AI technologies among non-experts on the other side, hinders effective evaluation and critique of possibly irreparable harm that these technologies may cause [55,73]. That makes understanding of ethical theories and ethical evaluation of situations influenced by AI crucial – not only for experts but also for non-experts [153]. Therefore, incorporating ethics in AI literacy assessments is increasingly common but not straightforward.

First, due to its nature and because there seldom is a 'right' or 'wrong', ethics is difficult to assess using conventional scales. Additionally, ethics and other humanities are often seen as 'soft skills', giving them side importance [140]. As a consequence, in many AI literacy assessments, ethics is not seamlessly integrated but given a supplemental role (e.g., [29,173]). Additionally, the field of ethics is complex, making it necessary to comprise many different and complex aspects under one term. The most frequently addressed ethical principles in the AI literacy assessment frameworks are privacy or surveillance ([97,107,128,167]), harm to people or general risks ([81,97,107,135]), diversity, bias and fairness [107,167], transparency and explainability [107,128,167], responsibility and accountability [107,128,150], reliability and safety [128], social good and societal challenges [81,128] as well as fear and trust [157]. Even though the importance of AI ethics is largely recognized in current AI literacy frameworks, ethics is not always *explicitly* addressed. For example, Suh and Ahn [163] do not mention terms related to ethics or morality explicitly in their work. Still, 6/26 items of their scale are implicitly based on moral values. Within the scale by Grassini [64], three of four items ask for the perception of the positive effects of AI on life, work, and humanity in general. Since the evaluation of positivity is influenced by (moral) values, the scale is based on an ethical foundation, even though the author does not term it explicitly.

In our framework, AI ethics literacy as a distinct horizontal dimension was adopted due to several considerations: First, we acknowledge the importance of ethics being an integral part of AI literacy. Ethics has emerged as an important aspect of AI literacy that both transcends categorizations of attitudes, behavior, and cognition (see Section 3.2) and represents an incremental addition to generic and domain-specific AI literacies. Ethical literacy and awareness in the context of AI technologies need to be reflected in every aspect of AI literacy and is therefore represented in its own dimension. Ethical AI literacy includes awareness of AI-related issues in personal and professional contexts. While there certainly are generic and domain-specific AI ethics competencies, we give ethics its own place in the framework without subsuming it in the other two categories and thus, making it visible. Furthermore, placing ethics as a horizontal dimension allows us to assess a wider range of different ethical aspects – structured according to the dimensions of competence of cognition, behavior and attitude ([176,177]; see Section 3.2). This allows us to address far more different aspects of AI ethics literacy, instead of giving it just one box in the matrix.

3.2. The vertical dimension – competence dimensions

3.2.1. The ABC approach

After explaining the important distinction between generic AI literacy, domain-specific AI literacy, and AI ethics literacy in the previous section, this section provides an overview of the assessment of literacy in terms of attitudes, behaviors, and cognitions as elements of a comprehensive understanding of competence. The triad of cognition ("knowledge"), behavior ("skills"), and attitudes (or "values") is not fundamentally new. Still, it has gained prominence in the debate on the concept of competence because it can be a condition for people's ability to solve situational problems in a flexible way [13,171].

The conceptualization of competence as an ABC (Attitude, Behavior, Cognition) model is rooted in Weinert's [176,177] concept of competence. Weinert defines competencies as "the cognitive abilities and skills that individuals possess or learn to use to solve particular problems, as well as the related motivational, volitional, and social dispositions and abilities to use the problem solutions successfully and responsibly in variable situations" ([176], p. 27 f.). Thus, Weinert's [176] concept of competence refers to the necessary prerequisites available to an individual or a group of individuals to successfully meet complex demands, particularly in professional positions, that target domain-specific competencies, as well as in the context of social roles or personal projects, which target generic competencies for domain-unspecific actions [100,176]. The prominent rise of AI can be positioned as such a complex demand for different professional domains and society, pointing to the need to think about the necessary cognitions, behaviors, and attitudes for generic AI literacy and domain-specific AI literacy at the same time.

Weinert's [176,177] definition of competence implies a distinction between cognition, behavior, and attitude as constituents of comprehensive competence, as he describes different components of competence that correspond to these categories. For example, Weinert [176] refers to cognition as "conceptual competence", which involves rule-based abstract knowledge about an entire domain, such as artificial intelligence. This includes explicit and declarative knowledge and understanding. Behavior is introduced by "procedural competence", which is about the availability of procedures and skills needed to apply conceptual competencies in concrete situations. This is consistent with the behavioral aspects, which focus on the practical application of skills and knowledge. Finally, attitudes are added to this conceptualization through Weinert's [176] description of "action competence", which includes the cognitive, motivational, and social prerequisites necessary for successful learning and action. This concept integrates cognitive skills, motivational tendencies, volitional control systems, personal value orientations, and social behaviors, thereby addressing the attitudinal component in addition to the cognitive and behavioral aspects required for a comprehensive understanding of competence. In sum, individuals show their competence if they use their knowledge ("cognitions") to guide their actions ("behaviors"), and if these actions are supported by values ("attitudes"). Consequently, competent behaviors may not be performed if the necessary skills are present, but personal attitudes counteract performance.

The ABC model can also be aligned with Bloom's and colleagues' well-established taxonomy of educational objectives [9,17,94]. Furthermore, ABC models can also be found in other research areas that strive to represent a holistic understanding of what we feel (attitude), think (cognition), and do (behavior) [168].

In the context of assessing AI literacy, the composition of competence through cognition, behavior, and attitudes was taken up by Ng et al. [128] in a recent study that addressed the limitations of previous assessments that primarily addressed cognitive aspects only. Consequently, they developed a questionnaire covering affective, behavioral, cognitive, and ethical aspects of AI literacy, the AILQ. The rigorous psychometric validation of this questionnaire suggests that this 4-factor solution to AI literacy may indeed be adequate. These defining elements of literacy are discussed in more detail in the following sections. Although we acknowledge the conceptualization of Ng et al. [128], we reflect the AI ethics component as a distinct literacy type alongside generic and domain-specific AI literacy, as research suggests that AI ethics literacy is itself constituted by cognitions, behaviors, and attitudes.

While moral reasoning and character building are important aspects of ethics education, their direct influence on behavior in critical situations or facing moral dilemmas remains unclear [47,71]. Consequently, a heightened focus on behavior within ethics and ethics education becomes essential to analyze how and why people make decisions in certain contexts [48,139]. Cognition in the context of ethics comprises the acquisition of knowledge and understanding of ethical principles and aspects. This dimension explores the role of the brain in moral reasoning and decision-making processes, enhancing the intellectual foundation necessary for ethical conduct. This is in line with Newberry [126], who condensed ethics-related learning goals in the context of engineering into three key dimensions: emotional engagement, intellectual engagement, and particular or discipline-specific knowledge. Emotional engagement involves the desire to be ethical, while intellectual engagement focuses on knowing how to be ethical, and discipline-specific knowledge is necessary for making ethical decisions. Hess and Fore [77] differentiate between *ethical sensitivity and awareness* (awareness of ethically problematic situations or issues), *ethical judgment, decision-making or imagination* (knowing how to reason or act ethically), and *ethical courage, confidence, or commitment* (being ethical). These aspects can be mapped to all three ABC components: attitude, behavior, and cognition. To make the single elements of the ABC competence approach clearer, each component (*Attitude, Behavior, Cognition*) is briefly described in more detail in the following sections.

3.2.2. Attitude

The special feature of Weinert's approach to competence lies, among other things, in the emphasis on affective aspects such as attitudes. Attitude encompasses an individual's perspective, mindset, and approach to work and life in general [8]. It includes characteristics such as motivation, enthusiasm, adaptability, resilience, and a willingness to learn and grow. A positive attitude can significantly increase the effectiveness with which one applies one's skills and knowledge [152]. In many professional and personal settings, attitude is considered an essential element of competence. A person with the necessary skills and knowledge may still underperform because of a negative attitude. On the other hand, a person with a positive attitude typically demonstrates greater adaptability and problem-solving skills, contributing to enhanced competence in various scenarios [1,2]. White [179, p. 317 argued: "that it is necessary to make competence a motivational concept, that there is a competence motivation". Such an aspect of competence is also related to self-efficacy 112 and forms beliefs about one's learning and performance. Attitudes, as a component of competence, influence behaviors and cognitions through expectations and interpretative schemata toward a subject matter (e.g., AI) 89. As a result, attitudes can also serve as volitional control systems in the form of motivational tendencies 38,181].

The attitudinal dimension in the context of AI literacy was also pointed out in the recent questionnaire by Ng et al. [128] under the dimension of *affective learning*, which also includes intrinsic motivation and self-efficacy. The attitudinal dimension refers to students' innate emotional and physiological changes toward AI. It includes elements such as interest, confidence, motivation, attitudes, and self-efficacy. Specifically, the affective learning dimension in their study includes four factors: Intrinsic motivation, self-efficacy, career interest, and confidence in learning AI. Taken together, this dimension aims to capture the emotional and motivational aspects of students' learning experiences, highlighting how students feel about and are driven to engage with AI topics. Within the DigComp 2.2 framework, requirements for citizens interacting with AI systems on the attitudinal dimension were captured as follows: human agency and control; critical yet open attitude; ethical considerations of usage [171].

Attitudes in the context of ethical literacy are also highly relevant. For example, attitudes, or emotions, play an indispensable role in moral deliberation and moral behavior [23]. Attitude, therefore, emerges as a necessary component for ethical decisions and ethical behavior and can take on many facets, for example: moral judgment [77], ethical sensitivity [19], or judging the relative importance of ethical principles, trust, risk and opportunity awareness of AI, usage intention, responsibility attribution, or normative expectations for political decisions on AI [91].

3.2.3. Behavior

As discussed earlier, competent behaviors refer to the practical skills, expertise, and procedural knowledge that enable an individual to perform specific tasks effectively. These skills are typically acquired and honed through hands-on practice and experiential learning. As such, they also form the basis for goal-directed behaviors and are often defined as procedural competencies, which include procedures and skills necessary to apply conceptual competencies (cognition) in concrete situations [66,159,176]. In addition, behavior related to competence can also be described as performance competence when performance indicators come into play [16].

Ng et al.'s [129] AILQ captured behavior through a dimension they called *behavioral learning*, which reflects behavioral engagement and cooperation in AI educational contexts. While this is certainly an important aspect of AI education, it does not represent AI-literate behaviors in terms of performance indicators. The behavioral dimension referred to as behavioral learning in the Ng et al. [128] study, refers to student actions, operational performance, and external behaviors that demonstrate active learning. This includes aspects such as course completion, behavioral intention, collaboration, and engagement. The behavioral learning dimension in their study is specifically divided into two factors: Students' behavioral engagement and collaboration to build relationships and pursue learning goals in an AI environment. According to the authors, these factors are designed to assess how students engage with and apply their learning in practical contexts, particularly in collaborative and active learning settings related to AI. DigComp 2.2′s requirements for citizens interacting with AI systems considered the behavioral dimension as the skill to use, interact with, and provide feedback to AI systems as end users, as well as to configure, supervise, and adapt AI systems (e.g., overwrite, tweak) [171].

For an assessment of ethical behavior, the learning goal(s) of the course (or knowledge testing) must be clear [76]. This ethical behavior can be judged either generally or based in accordance with ethical theories. Rest et al. [143] introduced a fictitious scenario to their participants and asked for their behavioral intentions. Answers were judged on deontological measures. Such an approach can help to measure morally right behavior but is bound to a theory from philosophical ethics. Instead, ethical courage, confidence, or commitment as being ethical [77] can be evaluated in the context of AI ethics both via behavioral intention as well as statements on actual ethical behavior.

3.2.4. Cognition

Although cognition is a term that can be conceptualized much more broadly, within concepts of competence, the term primarily targets declarative knowledge, such as the understanding and recognition of facts, data, concepts, and theories. It is essentially what an individual understands and thinks about a particular subject or field. This knowledge is typically acquired through education, training, reading, and various other learning methods. This type of knowledge is also sometimes referred to as conceptual competence [66,159].

Ng et al. [128] defined cognition within AI literacy as *cognitive learning* that reflects the knowing and understanding, applying, evaluating, and creating aspects of Bloom's taxonomy of the cognitive domain [9,17]. The cognitive dimension in the study by Ng et al. [128] focuses on students' achievement of knowledge and skills in artificial intelligence (AI). This dimension is broken down into three key factors that are consistent with Bloom's taxonomy of the cognitive domain [9,17]. These are: Lower-order thinking skills, which include knowing and understanding AI; Mid-order skills, which include using and applying AI; and Higher-order thinking skills, which include evaluating and creating AI. Therefore, the cognitive dimension aims to capture the range of cognitive skills from basic understanding to advanced application and creation in the context of AI. However, the cognitive learning dimension in Ng et al.'s [129] AILQ faced challenges in distinguishing certain subfactors, which led to the removal of overlapping items to achieve clearer discrimination. From a policy framework perspective, DigComp 2.2, in its requirements for citizens interacting with AI systems in their cognitive dimension, formulates the basic knowledge of being aware of what AI systems do and do not do, as well as understanding the benefits, limitations, and challenges of AI systems [171].

Cognitions within AI ethics imply knowledge about ethics in AI and shall assess how much people know about questions from philosophical ethics and more specific AI principles. In most common ethical frameworks for AI [138], the following ethical issues are addressed: general ethical aspects, privacy, fairness/bias, explainability, accountability, transparency, correctness/accuracy, diversity, robustness, reproducibility. The more granular the principles in a measurement are diversified, the greater the detail of the measurement. For an introductory course to AI for laypeople with a short measurement, a smaller set of principles to be measured might be more practical. Still, further diversification should be considered for advanced levels. Further, additionally including extra-ethical dimensions allows for an investigation of shifts between goal-oriented usage and moral values.

4. Applying the holistic AI literacy assessment matrix

In the previous chapter, we introduced our conceptual framework for structuring a holistic AI literacy assessment and thoroughly explored the theoretical grounding of its dimensions. In the following, we put this framework into practice by diving into the AI literacy (assessment) specificities of three concrete example domains: medicine, engineering, and education. AI literacy is highly relevant in each field and continues to gain relevance as more AI applications and human-AI collaborations permeate hospitals, factory floors, and classrooms. Therefore, we review the relevance and assessment specificities of each domain in Sections 4.1.1 to 4.1.3. Moreover, we provide example measurements (self-assessment Likert-scale items) for medicine-specific AI literacy, engineering-specific AI literacy, education-specific AI literacy, and AI ethics as well as generic AI literacy items in Table 2. To complement the exemplary items from Table 2, we review other measurement methods for a holistic assessment of AI literacy in Section 4.2.

4.1. Domain-specific AI literacy assessments

4.1.1. AI literacy assessment for the medical domain

One domain in which AI is already becoming increasingly important is the healthcare sector [75]. Particularly, doctors must possess the ability to interact with technological applications, which are at least partially supported by AI models [170]. In their literature review on medical students' AI literacy, Mousavi Baigi et al. [121] also divide AI literacy into three sub-areas of AI knowledge, AI attitudes, and AI skills. This subdivision makes particular sense in the medical field. While doctors need to understand how AI works, they mostly need to be able to deal with medical AI applications and be open to AI rather than fearful of it. Thus, it is essential to develop reliable and valid measurement instruments for investigating the AI literacy specific to medicine and among medical students, doctors, and other healthcare sector employees. The reliable assessment of healthcare provider's AI literacy is crucial, as AI systems applied in this field typically operate with patient data, raising not only ethical questions [41] but also directly impacting the well-being and recovery of patients. Examples of potential questions

Table 2
Holistic AI literacy assessment matrix – with example items from the domains of medicine, engineering, and education.

	Generic AI literacy	*Domain-specific AI literacy - medicine*	*Domain-specific AI literacy - engineering*	*Domain-specific AI literacy - education*	*AI Ethics literacy*
Knowledge/ Cognition Please indicate your agreement with the following statement, from 'Do not agree at all' to 'Completely agree': I can…	1. describe how machine learning models are trained, validated, and tested.[1] 2. explain how rule-based systems differ from machine learning systems.	1. explain why medical imaging is increasingly relying on convolutional neural networks. 2. discuss strengths and weaknesses of clinical AI applications.	1. assess the fields of application, advantages, and disadvantages of digital twins. 2. distinguish the significance of different performance metrics concerning supervised learning tasks in unbalanced data sets.	1. explain how an AI system reacts to students' errors and creates personalized learning paths with adapted exercises and learning materials. 2. discuss how training data can lead to bias against vulnerable groups of learners.	1. describe the effects of the black box problem. 2. differentiate the two main, different accounts of privacy violation.
Skills/ Behavior Please indicate your agreement with the following statement, from 'Do not agree at all' to 'Completely agree': I can…	1. assess if a problem can and should be solved with artificial intelligence methods. 2. describe experiences in which I interacted with AI in my everyday life.	1. use at least one AI application in my professional role as a physician. 2. critically assess the significance of the results of a clinical AI application.	1. describe an optimization problem including objectives and constraints. 2. explain the advantages of generative design in a CAD tool (i.e. Autodesk-Fusion).	1. use an AI system in formative assessment to automatically assess students' answers to problems and provide immediate individual feedback. 2. use large language models (LLMs) to customize texts for students with learning difficulties at different levels.	1. value ethical principles whenever using AI applications or products. 2. weigh privacy and information security issues whenever using AI applications or products.
Attitudes/ Values Please indicate your agreement with the following statement, from 'Do not agree at all' to 'Completely agree':	1. Society will reap the benefits of a future filled with artificial intelligence. 2. I would feel uneasy if I was given a job where I had to use AI.	1. I fear that AI systems are going to replace medical imaging specialists in the next few years. 2. The use of AI in healthcare allows physicians to spend more time with their patients.	1. I am open to incorporating AI-driven solutions in engineering projects to optimize decision-making and problem-solving. 2. I value the role of human experience in engineering tasks and am cautious about relying too heavily on AI-driven decision-making.	1. AI in teaching can be a useful resource to facilitate differentiated teaching. 2. Students should be allowed to use LLM-based AI when creating texts for homework.	1. It is ethical for AI systems to make decisions that significantly impact individuals without human oversight. 2. AI systems should always be transparent in their decision-making processes, especially when their decisions affect individuals or society.

[1] From: Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T. [97]. Development of the "Scale for the assessment of non-experts' AI literacy"–An exploratory factor analysis. *Computers in Human Behavior Reports, 12*, 100338.

for assessing medicine-specific AI literacy are provided in Table 2. It should be noted that the measurement modality (e.g., self-assessment vs. multiple-choice test) should be adjusted according to the specific question. If the measurement holds no immediate significance for the respondents, a self-assessment is sufficient. In the medical context, this would be applicable if a healthcare institution (e.g., a hospital) aimed to gauge the AI literacy of its employees. However, if the measurement affects the respondent, a test procedure should be employed with answers that can be clearly categorized as correct or incorrect. An example of such a scenario would be measuring the medicine-specific AI literacy of medical students as part of an exam or as part of a job evaluation for physicians.

4.1.2. AI literacy assessment for the engineering domain

As AI becomes more pervasive, the demand for professionals trained in AI is expected to grow [72,141]. This is especially true for engineering, where AI is already being used in various areas such as autonomous driving, manufacturing, disaster risk management, and smart buildings. The rise of Industry 4.0, driven by AI, necessitates a shift in engineering education [26] towards advanced STEM knowledge and digital competencies, including AI literacy [69,117]. In this context, engineering tasks are closely linked to societal challenges, as demonstrated by frameworks like the Sustainable Development Goals (SDGs) by the United Nations [122,172], the NAE Grand Challenges for Engineering (National Academy of Engineering (NAE)), and the EU's ESG (Environment, Social, and Governance) Taxonomy Objectives (European Commission). Training individuals working with AI is crucial to instilling the right values, addressing the responsibility gap, and enabling them to identify potential harms. When developing AI literacy, engineering-specific competencies can be found in all competence dimensions of the presented approach: There is engineering-specific knowledge, for example about digital twins or autonomous driving, as well as certain practices or tools that are used specifically in the field of engineering. In addition, the attitudes of engineers towards AI play a major role, especially regarding societal challenges. In this way, the approach presented emphasizes the increasing importance of AI in engineering to train engineers to use AI in a socially responsible way [90,117].

4.1.3. AI literacy assessment for the educational domain

Especially with the emergence of large language models (LLMs), the challenges and risks that AI poses to the education system have been widely discussed (e.g., [33,58,80,88]). This is despite the fact that AI has long since found its way into the increasingly data-driven education system [36,98] and holds great potential for personalized learning. For example, chatbots have already been used for educational purposes in recent years [96]. The use of machine learning in the context of educational data mining processes has been around for several years in the context of large-scale international studies such as TIMSS or PISA [79,156]. In the design of adaptive intelligent tutoring systems for personalized learning, research and development work based on artificial intelligence models has also been carried out for over a decade [11,63], also in specific domains such as mathematics [27]. AI can be used here, for example, to create curricula or as a teaching assistant [80]. Educators around the world can use AI tools such as speech recognition or machine translation systems to provide adapted learning opportunities to students with disabilities, multilingual learners, or others who can benefit from personalized learning environments, and to enable them to participate in the classroom [28]. AI large language models can also be used in school learning to personalize texts and other instructional materials. However, these new opportunities do not come without risks [124]. Of paramount importance for AI in education is that, in addition to the known risks to privacy and data security, AI could pose new risks, such as the risk of scaling pattern recognition and automation leading to "algorithmic discrimination" (e.g., systematic inequity in learning opportunities or resources recommended to certain groups of students) [28]. It is therefore essential for teachers to acquire AI-related skills as part of their digital teaching skills. For example, they need to understand how intelligent tutoring systems work in order to manage automated feedback in a way that promotes learning and to create appropriate support plans for learners. They will also need to learn functional prompt engineering strategies to make targeted use of generative AI language models to adapt texts or systematically vary tasks [88]. Finally, privacy issues and the dependence of AI-based learning recommendations on training data must be understood to prevent harm to marginalized students and to identify systematic disadvantages or biases. Finally, despite critical attitudes, teachers must also have positive attitudes toward the benefits of AI and trust the technology to use it productively and feel well prepared to use AI in the classroom, which means they must also acquire AI-related affective skills [125].

4.2. Alternative assessment methods for the AI literacy matrix

Our developed holistic AI literacy assessment framework demonstrates that AI literacy is a multifaceted construct, spanning not only different domains but also different competence components along the ABC dimensions. Due to these different facets and components, different methods are required for a valid and reliable assessment and measurement of the relevant aspects of AI literacy for a given context. In Table 2 , we exemplified a variety of Likert-type items intended for a self-assessment. However, self-assessed Likert-type items are only one method to measure AI literacy, which, despite its advantages of easy deployment and comprehension, also has severe drawbacks, such as human biases in self-assessment [95]. As such, we want to emphasize that this method is only one from a potentially large toolbox of measures. Different competence dimensions of holistic AI literacy, like cognition and behavior, tend to be measured better by different methods [6,16]. For example, knowledge can be easily measured with a multiple-choice test, whereas actual behavior could be better measured with an observation. However, these relationships between measurement methods and competence dimensions are not exclusive, i.e., there are no 1:1 relationships. Likert-type items can measure affective components as well as cognitive components and behavioral intentions. In order to assess and measure AI literacy appropriately, one should first use the developed conceptual framework to decide which component in which domain is most relevant to be measured and then decide upon an appropriate measure.

So far, the measurement landscape of AI literacy is quite scarce. The majority of developed instruments are Likert-type self-assessments (e.g. [97,128,29,134,173]). Beyond that, some initial research ventured into developing objective tests, namely multiple-choice tests (e.g., [81,175]). Whereas these current objective tests cover mostly generic AI literacy aspects, such measurements are also suitable in principle for different domains. For example, in an educational setting like teacher education, an objective measurement item could be designed as illustrated in Fig. 1.

Another measure, which we believe to be promising regarding its applicability and explanatory power based on its usage in other research fields, would be a situational judgment test (SJT). SJTs are increasingly used to measure behavioral intentions and simulate real-world performance, making them an effective supplement to cognitive tests for competency assessment [102,148,178]. They offer realistic scenarios to assess different knowledge dimensions, using vignettes in text or video formats that bridge theoretical knowledge and practical application [106,114,120,142]. The involvement of domain experts in vignette development thereby ensures scenario relevance and authenticity, helping counteract respondent faking [131,137]. SJTs present hypothetical scenarios to evaluate participants' decision-making and behavioral intentions, acting as "low-fidelity simulations" of real behavior [21,119]. Responses are scored against expert norms, lending credibility and objectivity to the results [178]. In AI literacy assessments, SJTs could offer a practical solution for measuring specific

"Question: You use an LLM-based AI system that is able to explain concepts. How can this system be used most effectively in the classroom to improve student understanding?

- A) By using the system to do all the explaining so that the teacher no longer needs to give direct instruction.
- B) Using the system exclusively outside the classroom to provide homework help to students.
- C) Use AI only for advanced students and use classical teaching methods for students with learning difficulties.
- D) Using the system as a supplement to the teacher to explain concepts in different ways to support different learning styles."

Fig. 1. Multiple-choice-test item for AI literacy in the educational domain.

competencies, especially behavior, not captured by traditional tests or self-assessments [56,161]. An exemplary SJT item for the medical domain could be designed like the one shown in Fig. 2.

Further options to catch more behavioral data in AI literacy could be performance data in practical applications or the recording of process data while interacting with certain AI technologies or working within AI-based environments, in the form of event log data with time stamps, browsing/interaction history and eye movements.

5. Discussion

The holistic AI literacy assessment matrix presented in this paper possesses its specific strengths as well as limitations. Therefore, this section will reflect on the work presented here and critically discuss which aspects are promising and which need further refinement. As a result of this process, a number of questions have arisen for a future research agenda in the area of AI literacy research.

With the concept presented here, we aim to inspire and assist the development of more refined AI literacy assessment instruments that particularly consider domain-specific differences between different forms of AI literacy. As it is foreseeable that AI will fundamentally change the future of education in every subject area [18,36,110,146], and that future professions and work will be equally affected [82,133,174,187], there is an urgent need for assessments that take into account this very feature of domain-specificity, as the availability of appropriate assessments is a necessary prerequisite for targeted AI educational programs, interventions, and curricula. We therefore propose to use the holistic AI literacy assessment matrix to guide the development of future instruments in the manner of an item development heuristic [37,164,188]. Following a heuristic based on our matrix makes it possible to distinguish between the generic, domain-specific, and ethical types of AI literacy, as well as the cognitive, behavioral, and attitudinal dimensions of competence. Certainly, not every aspect is needed in every AI literacy assessment instrument, but following a straightforward item development heuristic based on this AI literacy matrix allows one to clearly position one's own contribution to AI literacy measurement, while at the same time clearly distinguishing aspects that are not intended to be captured within a given instrument.

Since the particular strength of the AI literacy matrix approach is its distinction between generic and domain-specific AI literacy types, as well as AI ethics literacy, this conceptualization of AI literacy may also inspire future AI educational efforts and the urgently needed creation of domain-specific AI learning opportunities [93,103,116,118,151]. In educational contexts, distinguishing between literacy types and competence dimensions not only provides a basis for improved assessment methods but also offers an opportunity to develop assessment instruments that follow constructive alignment approaches [7,15,109]. In keeping with the constructive alignment method, it's important to plan ahead for the methods and ways in which learning objectives will be assessed, so that future educational efforts can use the provided holistic AI literacy matrix and target their efforts to specific constellations intended to be taught, e.g., cognitive and attitudinal aspects in the

"Situation: You are a doctor using an AI tool for patient diagnosis. The tool occasionally suggests rare conditions that seem unlikely. What would you do to handle this situation?:

- A) Strictly follow the AI's suggestions, assuming its advanced capabilities.
- B) Ignore the AI suggestions and rely solely on personal medical judgment.
- C) Use the AI's suggestions as a starting point for further investigation.
- D) Consult a colleague each time the AI suggests a rare condition."

Fig. 2. Situational judgement test item for AI literacy in the medical domain.

domain of medicine, or cognitive aspects and behaviors in engineering. Therefore, the provided matrix can also be used to develop AI educational learning opportunities, such as courses, in a more targeted and fine-grained perspective.

While our approach to a more holistic AI literacy assessment seems promising, it is beyond the scope of this conceptual paper to develop a comprehensive item pool and usable scales. This work does not represent a developed scale, but rather a practical guiding framework for future developments in AI literacy assessment. Therefore, our conceptualization of AI literacy as consisting of generic, domain-specific, and AI ethical literacies along the ABC dimensions lacks rigorous psychometric validation, a task that must be addressed in future research. Such empirical evidence is central to establishing generic AI literacy, domain-specific AI literacy, and AI ethics literacy as distinct constructs that require further research, potentially serving precise constructive alignment goals for teaching, learning, and assessment in educational settings.

In particular, psychometric validation needs to further explore the uniqueness and incremental value of domain-specific AI literacy over generic AI literacy, and whether such a distinction holds over time [190]. Our conceptualization of AI ethics literacy also suffers from this lack of validation. While Ng et al. [128] position ethics along the ABC dimensions as ABCE, we proposed to position ethics as an equivalent type of literacy along with generic and domain-specific AI literacy. This decision for AI ethics literacy as a distinct category is supported by the fact that not only Ng et al. [128], but most previous conceptualizations of AI literacy have all crystallized an "AI ethics" factor in their factor analytic evaluations that is independent of the other categories (AI knowledge, etc.), making it a distinct factor that recurs across different conceptualizations of AI literacy.

However, as we pointed out in Section 3.1.3, this approach also has its limitations, as AI ethics literacy, if operationalized and psychometrically tested, might also show cross-loadings with generic AI literacy and domain-specific AI literacy. We acknowledge that our approach still gives ethics a complementary role in the AI literacy framework. Furthermore, this approach cannot necessarily account for all the ethical details within generic and domain-specific AI literacies.

6. Outlook and future research agenda

The discussion of the holistic AI literacy assessment matrix, in terms of its strengths and limitations outlined above, points towards a future research agenda. First, we suggest developing more AI literacy assessment instruments, that use the suggested AI literacy matrix, to do the broadness, diversity, and importance of the construct of AI literacy justice. Therefore, we urge academics to use our holistic AI literacy matrix to develop more refined tools that are able to capture more aspects of AI literacy, especially domain-specific AI literacy, and also to develop measurement tools that are more attuned to behavior, which is currently missing from most AI literacy tools. Alternative measurement methods like SJTs might also be fruitful approaches to a more differentiated understanding of AI literacy as a construct [101]. Second, AI literacy instruments that were developed according to this matrix as well as existing AI literacy instruments can be used to validate this holistic framework and provide insights into the nature and the relationships among generic, domain-specific, and ethical AI literacy [111]. Further open questions regarding validity concern the predictive and criterion validity of our holistic AI literacy approach, which is not a limitation per se, but can rather be seen as another future research question within AI literacy research. Two aspects in particular arise here. First, questions arise about the competencies and skills that serve as antecedents of AI literacy, i.e., what role does the development of basic digital literacy, data literacy, or programming skills play in the different types of AI literacies and competence dimensions of AI literacy proposed in this work [61,175]? Also, what is the convergent validity of different types of AI literacy compared to existing AI literacy instruments? Second, how does AI literacy in its different dimensions and its different literacy types affect human-AI interactions, i.e., how do their patterns of use of AI technology differ qualitatively from those of less AI literate people? [31,43,54,115].

As such, future research points towards the need for environments that allow for the exploration of various indicators and influencing factors relevant to the development of generic and domain-specific AI literacy. AI MOOCs may be a suitable setting for such efforts, as contextual factors (e.g., type/number of courses completed), prior AI and/or domain education, and other measures of survey, performance, or tracking data may provide important insights into the antecedents and implications of AI literacy. A set of items designed according to our matrix could also be tested in different learning opportunities facilitated by an AI MOOC platform. As a result, it could be explored how different aspects of AI literacy relate to each other, potentially providing important insights into the composition of the construct of AI literacy. Additionally, this raises the question of successful models for teaching AI literacy in educational settings. For example, is it more promising to teach holistic AI literacy using a respective holistic approach, or can people also acquire holistic AI literacy using an atomistic approach in which individual aspects are acquired in a focused manner?

Finally, AI literacy research should span other relevant domains, not just the three chosen here (medicine, engineering, and education). The choice of these three particular domains reflects the interdisciplinary nature of the group involved in this work, as well as the fact that these domains are already heavily impacted by AI and are already engaged in a lively scientific discourse about the role of AI within their professional domain [26,41,75,80,121,141]. However, if AI literacy is to be developed across all subjects and professional domains, we suggest and encourage AI literacy research in domains that are not currently found in the typical AI literacy research landscape. Subsequently, we envision that the matrix we provide, and in particular the introduction of domain-specific AI literacy, a crucial aspect currently missing from existing frameworks, can stimulate and guide thinking about the specific needs for AI literacy in different professional domains, and align domain-specific AI literacy with specific educational and workforce needs.

7. Conclusion

Concluding this present paper, to use this AI literacy matrix practically, it is necessary to decide which aspects, constituents, and components are appropriate to adequately reflect the construct of AI literacy. The main components within this work have been described as generic AI literacy, domain-specific AI literacy, and AI ethics literacy, each consisting of cognitions, behaviors, and attitudes as different competence dimensions. In particular, it was intended to illustrate how AI literacy can serve different purposes for the different domains of medicine, engineering, and education, and the associated AI-related competency requirements within each domain. It is hoped that the holistic AI literacy assessment matrix provided here will contribute to the much-needed advancement of AI literacy measurement tools, particularly for domain-specific AI literacy, as for this area a large research gap remains to date and could be of enormous importance if we are to successfully integrate AI literacy into various subjects within educational institutions, as well as foster the development of AI literacy for different professional work domains. If we, as educators and researchers, envision AI literacy for all, this means that we need to broaden our scope beyond generic AI literacy – which of course is still very important – but we also need conceptualizations and assessment tools of AI literacy that adequately capture domain-specificity and ethical aspects of AI. Establishing AI literacy in different domains is key to enabling a hybrid intelligent paradigm [44,85] that aligns human-AI interactions in a collaborative and co-creative way and benefits every student, worker, and citizen.

Declaration of generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work the author(s) used DEEPL Write in order to improve readability and streamline language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Ajzen I. From intentions to actions: a theory of planned behavior. J. Kuhl (Ed.). Action control: from cognition to behavior. Berlin Heidelberg: Springer; 1985. p. 11–39. https://doi.org/10.1007/978-3-642-69746-3_2.
[2] Ajzen I. The theory of planned behavior. Organ Behav Hum Decis Process 1991; 50(2):179–211. https://doi.org/10.1016/0749-5978(91)90020-T.
[3] Alexander PA, Jablansky S, Singer LM, Dumas D. Relational reasoning. Policy Insights Behav Brain Sci 2016;3(1):36–44. https://doi.org/10.1177/2372732215622029.
[4] Alexander PA, Judy JE. The interaction of domain-specific and strategic knowledge in academic performance. Rev Educ Res 1988;58(4):375–404. https://doi.org/10.3102/00346543058004375.
[5] Alekseeva L, Azar J, Giné M, Samila S, Taska B. The demand for AI skills in the labor market. Labour Econ 2021;71:102002. https://doi.org/10.1016/j.labeco.2021.102002.
[6] Allen, J.P., & van der Velden, R.K.W. (2005). The role of self-assessment in measuring skills. https://cris.maastrichtuniversity.nl/en/publications/the-role-of-self-assessment-in-measuring-skills.
[7] Ali L. The design of curriculum, assessment and evaluation in higher education with constructive alignment. J Educ E Learn Res 2018;5(1):72–8. https://eric.ed.gov/?id=ej1173088.
[8] Allport GW. Attitudes. A handbook of social psychology. Clark University Press; 1935. p. 798–844.
[9] Anderson LW, Krathwohl DR. A taxonomy for learning, teaching, and assessing: a revision of Bloom's Taxonomy of educational objectives. Longman; 2001 (Abridged ed.).
[10] Anthonysamy L, Koo AC, Hew SH. Self-regulated learning strategies in higher education: fostering digital literacy for sustainable lifelong learning. Educ Inf Technol 2020;25(4):2393–414. https://doi.org/10.1007/s10639-020-10201-8 (Dordr).
[11] Graesser AC, VanLehn K, Rose CP, Jordan PW, Harter D. Intelligent tutoring systems with conversational dialogue. AI Mag 2001;22(4):39. https://doi.org/10.1609/aimag.v22i4.1591.
[12] Audrin C, Audrin B. Key factors in digital literacy in learning and education: a systematic literature review using text mining. Educ Inf Technol 2022;27(6): 7395–419. https://doi.org/10.1007/s10639-021-10832-5 (Dordr).
[13] Baartman LK, de Bruijn E. Integrating knowledge, skills and attitudes: conceptualising learning processes towards vocational competence. Educ Res Rev 2011;6(2):125–34. https://doi.org/10.1016/j.edurev.2011.03.001.
[14] Bewersdorff A, Zhai X, Roberts J, Nerdel C. Myths, mis- and preconceptions of artificial intelligence: a review of the literature. Comput Educ Artif Intell 2023;4: 100143. https://doi.org/10.1016/j.caeai.2023.100143.
[15] Biggs J. Enhancing teaching through constructive alignment. High Educ 1996;32 (3):347–64. https://doi.org/10.1007/BF00138871 (Dordr).
[16] Blömeke S, Gustafsson JE, Shavelson RJ. Beyond dichotomies. Z Psychol 2015; 223(1):3–13. https://doi.org/10.1027/2151-2604/a000194.
[17] Bloom BS, Engelhart MD, Furst EJ, Hill WH, Krathwohl DR. Taxonomy of educational objectives: the classification of educational goals: handbook I: cognitive domain. David McKay Company; 1956.
[18] Bond M, Khosravi H, Laat Mde, Bergdahl N, Negrea V, Oxley E, Pham P, Chong SW, Siemens G. A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour. Int J Educ Technol High Educ 2024;21(1):1–41. https://doi.org/10.1186/s41239-023-00436-z.
[19] Borenstein J, Drake M, Kirkman R, Swann J. The test of ethical sensitivity in science and engineering (Tesse): a discipline specific assessment tool for awareness of ethical issues. In: Proceedings of the 2008 annual conference & exposition proceedings; 2008. https://doi.org/10.18260/1-2-3253 (13.1270.1-13.1270.10)ASEE Conferences.
[20] Borenstein J, Howard A. Emerging challenges in AI and the need for AI ethics education. AI Ethics 2021;1(1):61–5. https://doi.org/10.1007/s43681-020-00002-7.
[21] Borman WC, Motowidlo SJ. Task performance and contextual performance: the meaning for personnel selection research. Hum Perform 1997;10(2):99–109. https://doi.org/10.1207/s15327043hup1002_3.
[22] Boyatzis RE. Competencies in the 21st century. J Manag Dev 2008;27(1):5–12. https://doi.org/10.1108/02621710810840730.
[23] Bratton, V.K. (2004). Affective morality: the role of emotions in the ethical decision-making process. https://search.proquest.com/openview/2c634b42ee5860606e51b58669ee85ce/1?pq-origsite=gscholar&cbl=18750&diss=y.
[24] Bromme R. Kompetenzen, funktionen und unterrichtliches handeln des lehrers. F. E. Weinert (Hrsg.). Enzyklopädie der psychologie: pädagogische psychologie, Bd. 3: psychologie des unterrichts und der schule. Göttingen: Hogrefe; 1997. p. S.177–212.
[25] Bromme R. Der lehrer als experte: zur psychologie des professionellen Wissens. Standardwerke aus psychologie und pädagogik - reprints: band 7. Waxmann; UTB GmbH; 2014. https://elibrary.utb.de/doi/book/10.31244/9783830980421.
[26] Bühler MM, Jelinek T, Nübel K. Training and preparing tomorrow's workforce for the fourth industrial revolution. Educ Sci 2022;12(11):782. https://doi.org/10.3390/educsci12110782 (Basel).
[27] Bywater JP, Chiu JL, Hong J, Sankaranarayanan V. The teacher responding tool: scaffolding the teacher practice of responding to student ideas in mathematics classrooms. Comput Educ 2019;139(1):16–30. https://www.learntechlib.org/p/209941/.
[28] Cardona MA, Rodríguez RJ, Ishmael K. Artificial intelligence and the future of teaching and learning: insights and recommendations. Department of Education; 2023. United States, https://digital.library.unt.edu/ark:/67531/metadc2114121/.
[29] Carolus A, Koch MJ, Straka S, Latoschik ME, Wienrich C. MAILS - Meta AI literacy scale: development and testing of an AI literacy questionnaire based on well-founded competency models and psychological change- and meta-competencies. Comput Hum Behav Artif Hum 2023;1(2):100014. https://doi.org/10.1016/j.chbah.2023.100014.
[30] Casal-Otero L, Catala A, Fernández-Morante C, Taboada M, Cebreiro B, Barro S. Ai literacy in K-12: a systematic literature review. Int J STEM Educ 2023;10(1): 1–17. https://doi.org/10.1186/s40594-023-00418-7.
[31] Cetindamar D, Kitto K, Wu M, Zhang Y, Abedin B, Knight S. Explicating AI literacy of employees at digital workplaces. IEEE Trans Eng Manag 2024;71: 810–23. https://doi.org/10.1109/tem.2021.3138503.
[32] Chan CK, Chen SW. Students' perceptions on the recognition of holistic competency achievement: a systematic mixed studies review. Educ Res Rev 2022; 35:100431. https://doi.org/10.1016/j.edurev.2021.100431.
[33] Chiu TKF. The impact of Generative AI (GenAI) on practices, policies and research direction in education: a case of ChatGPT and Midjourney. Interact Learn Environ 2023:1–17. https://doi.org/10.1080/10494820.2023.2253861.
[34] Chiu TKF, Meng H, Chai CS, King I, Wong S, Yam Y. Creation and evaluation of a pretertiary artificial intelligence (AI) curriculum. IEEE Trans Educ 2022;65(1): 30–9. https://doi.org/10.1109/TE.2021.3085878.
[35] Chiu TK. Future research recommendations for transforming higher education with generative AI. Comput Educ Artif Intell 2024;6:100197. https://doi.org/10.1016/j.caeai.2023.100197.
[36] Chiu TK, Xia Q, Zhou X, Chai CS, Cheng M. Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. Comput Educ Artif Intell 2023;4:100118. https://doi.org/10.1016/j.caeai.2022.100118.
[37] Choi SW, Lim S, van der Linden WJ. TestDesign: an optimal test design approach to constructing fixed and adaptive tests in R. Behaviormetrika 2022;49:191–229. https://doi.org/10.1007/s41237-021-00145-9.
[38] Cialdini RB, Petty RE, Cacioppo JT. Attitude and attitude change. Annu Rev Psychol 1981;32(1):357–404. https://doi.org/10.1146/annurev.ps.32.020181.002041.
[39] Coeckelbergh M. Artificial intelligence, responsibility attribution, and a relational justification of explainability. Sci Eng Ethics 2020;26(4):2051–68. https://doi.org/10.1007/s11948-019-00146-8.

[40] Crawford K. The atlas of AI: power, politics, and the planetary costs of artificial intelligence. Yale University Press; ProQuest; 2021.
[41] Dalton-Brown S. The ethics of medical AI and the physician-patient relationship. Camb Q Healthc Ethics CQ 2020;29(1):115–21. https://doi.org/10.1017/S0963180119000847. The International Journal of Healthcare Ethics Committees.
[42] Davis M. Integrating ethics into technical courses: micro-insertion. Sci Eng Ethics 2006;12(4):717–30. https://doi.org/10.1007/s11948-006-0066-z.
[43] Dell'Acqua, F., McFowland, E., Mollick, E.R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K.R. (2023). Navigating the jagged technological frontier: field experimental evidence of the effects of AI on knowledge worker productivity and quality. 10.2139/ssrn.4573321.
[44] Dellermann D, Ebel P, Söllner M, Leimeister JM. Hybrid intelligence. Bus Inf Syst Eng 2019;61(5):637–43. https://doi.org/10.1007/s12599-019-00595-2.
[45] Dignum V. Responsibleartificial intelligence: how to develop and use AI in a responsible way. 1st ed. Springer International Publishing; 2019. https://doi.org/10.1007/978-3-030-30371-6. 2019Artificial Intelligence.
[46] DiSessa AA. Changing minds: computers, learning and literacy. The Mit Press; 2001.
[47] Doris JM. Lack of character: personality and moral behavior. Cambridge University Press; 2002. https://doi.org/10.1017/CBO9781139878364.
[48] Drumwright M, Prentice R, Biasucci C. Behavioral ethics and teaching ethical decision making. Decis Sci J Innov Educ 2015;13(3):431–58. https://doi.org/10.1111/dsji.12071.
[49] Durmaz A, Dursun İ, Kabadayi ET. Mitigating the effects of social desirability bias in self-report surveys. A. Ippolito, C. Inglese, & S. Chakraborty (Eds.). Advances in library and information science (ALIS) book series: 2020: 4. Challenges of globalization and inclusivity in academic research. IGI Global; 2024. p. 146–85. https://doi.org/10.4018/978-1-7998-1025-4.ch007.
[50] Eaton E, Koenig S, Schulz C, Maurelli F, Lee J, Eckroth J, Crowley M, Freedman RG, Cardona-Rivera RE, Machado T, Williams T. Blue sky ideas in artificial intelligence education from the EAAI 2017 new and future AI educator program. AI Matters 2018;3(4):23–31. https://doi.org/10.1145/3175502.3175509.
[51] Epstein RM, Hundert EM. Defining and assessing professional competence. JAMA 2002;287(2):226–35. https://doi.org/10.1001/jama.287.2.226.
[52] Ericsson KA. The influence of experience and deliberate practice on the development of superior expert performance. K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman (Eds.). The Cambridge handbook of expertise and expert performance. Cambridge: University Press; 2012. p. 683–704. https://doi.org/10.1017/CBO9780511816796.038. Repr.
[53] Eslami M, Vaccaro K, Lee MK, Elazari Bar On A, Gilbert E, Karahalios K. User attitudes towards algorithmic opacity and transparency in online reviewing platforms. S. Brewster, G. Fitzpatrick, A. Cox, & V. Kostakos (Eds.). In: Proceedings of the 2019 CHI conference on human factors in computing systems. ACM; 2019. p. 1–14. https://doi.org/10.1145/3290605.3300724.
[54] Faruqe, F., Watkins, R., & Medsker, L. (2021). Competency model approach to AI literacy: research-based path from initial framework to model. http://arxiv.org/pdf/2108.05809.pdf.
[55] Fast E, Horvitz E. Long-term trends in the public perception of artificial intelligence. In: Proceedings of the AAAI conference on artificial intelligence. 31; 2017. https://doi.org/10.1609/aaai.v31i1.10635.
[56] Fisher DM, Good S, Toich MJ, Schutt E. Measuring moral disengagement with a situational judgment test: advancing the assessment of an important workplace construct. Int J Sel Assess 2021;29(1):114–33. https://doi.org/10.1111/ijsa.12318.
[57] Fraillon J, Ainley J, Schulz W, Friedman T, Duckworth D. Preparing for life in a digital world: IEA international computer and information literacy study 2018 international report. 1st ed. Springer International Publishing; 2020. https://doi.org/10.1007/978-3-030-38781-5. 2020.
[58] Fütterer T, Fischer C, Alekseeva A, Chen X, Tate T, Warschauer M, Gerjets P. Chatgpt in education: global reactions to AI innovations. Sci Rep 2023;13(1):15310. https://doi.org/10.1038/s41598-023-42227-6.
[59] Gal I. Adults' statistical literacy: meanings, components, responsibilities. Int Stat Rev 2002;70(1):1. https://doi.org/10.2307/1403713.
[60] Ghallab M. Responsible AI: requirements and challenges. AI Perspect 2019;1(1):1–7. https://doi.org/10.1186/s42467-019-0003-z.
[61] Gillath O, Ai T, Branicky MS, Keshmiri S, Davison RB, Spaulding R. Attachment and trust in artificial intelligence. Comput Hum Behav 2021;115:106607. https://doi.org/10.1016/j.chb.2020.106607.
[62] Gilster P. Digital literacy. New York: Wiley Computer Publications; 1997.
[63] Graesser AC, Hu X, Sottilare R. Intelligent tutoring systems. F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.). International handbook of the learning sciences. Routledge; 2018. p. 246–55. https://doi.org/10.4324/9781315617572-24.
[64] Grassini S. Development and validation of the AI attitude scale (AIAS-4): a brief measure of general attitude toward artificial intelligence. Front Psychol 2023;14:1191628. https://doi.org/10.3389/fpsyg.2023.1191628.
[65] Greenhill AT, Edmunds BR. A primer of artificial intelligence in medicine. Tech Innov Gastrointest Endosc 2020;22(2):85–9. https://doi.org/10.1016/j.tgie.2019.150642.
[66] Greeno JG, Riley MS, Gelman R. Conceptual competence and children's counting. Cogn Psychol 1984;16(1):94–143. https://doi.org/10.1016/0010-0285(84)90005-7.
[67] Gruber H, Harteis C, Rehrl M. Professional learning: erfahrung als grundlage von handlungskompetenz. Bild Erzieh 2006;59(2):193–204. https://doi.org/10.7788/bue.2006.59.2.193.
[68] Gruber H, Mandl H. Expertise und erfahrung. H. Gruber & A. Ziegler (Eds.). Expertiseforschung: theoretische und methodische Grundlagen. VS Verlag für Sozialwissenschaften; 1996. p. 18–34. https://doi.org/10.1007/978-3-663-12111-4_2. Imprint.
[69] Grybauskas A, Stefanini A, Ghobakhloo M. Social sustainability in the age of digitalization: a systematic literature review on the social implications of industry 4.0. Technol Soc 2022;70:101997. https://doi.org/10.1016/j.techsoc.2022.101997.
[70] Haefner N, Parida V, Gassmann O, Wincent J. Implementing and scaling artificial intelligence: a review, framework, and research agenda. Technol Forecast Soc Change 2023;197:122878. https://doi.org/10.1016/j.techfore.2023.122878.
[71] Haidt J. Moral psychology for the twenty-first century. J Moral Educ 2013;42(3):281–97. https://doi.org/10.1080/03057240.2013.817327.
[72] Harari YN. Reboot for the AI revolution. Nature 2017;550(7676):324–7. https://doi.org/10.1038/550324a.
[73] Hardt M, Narayanan A. Fairness and machine learning: limitations and opportunities. The MIT Press; 2023.
[74] Hashemian G, Loui MC. Can instruction in engineering ethics change students' feelings about professional responsibility? Sci Eng Ethics 2010;16(1):201–15. https://doi.org/10.1007/s11948-010-9195-5.
[75] Haug CJ, Drazen JM. Artificial intelligence and machine learning in clinical medicine, 2023. N Engl J Med 2023;388(13):1201–8. https://doi.org/10.1056/NEJMra2302038.
[76] Hess JL, Beever J, Iliadis A, Kisselburgh LG, Zoltowski CB, Krane MJM, Brightman AO. An ethics transfer case assessment tool for measuring ethical reasoning abilities of engineering students using reflexive principlism approach. In: Proceedings of the 2014 IEEE frontiers in education conference (FIE). IEEE; 2014. p. 1–5. https://doi.org/10.1109/FIE.2014.7044441.
[77] Hess JL, Fore G. A systematic literature review of US engineering ethics interventions. Sci Eng Ethics 2018;24(2):551–83. https://doi.org/10.1007/s11948-017-9910-6.
[78] Heyder T, Posegga O. Extending the foundations of AI literacy. In: Proceedings of the ICIS 2021; 2021. https://aisel.aisnet.org/icis2021/is_future_work/is_future_work/9.
[79] Hilbert S, Coors S, Kraus E, Frei M, Lindl A, Wild J, Krauss S, Goretzko D, Bischl B, Stachl C. Machine learning for the educational sciences. Rev Educ 2021;9(3):e3310. Sven.
[80] Holmes W, Miao F, UNESCO. Guidance for generative AI in education and research. UNESCO Publishing; 2023.
[81] Hornberger M, Bewersdorff A, Nerdel C. What do university students know about Artificial Intelligence? Development and validation of an AI literacy test. Comput Educ Artif Intell 2023;5:100165. https://doi.org/10.1016/j.caeai.2023.100165.
[82] Howard J. Artificial intelligence: implications for the future of work. Am J Ind Med 2019;62(11):917–26. https://doi.org/10.1002/ajim.23037.
[83] Jacob SR, Warschauer M. Computational thinking and literacy. J Comput Sci Integr 2018;1(1). https://doi.org/10.26716/jcsi.2018.01.1.1.
[84] Jang Y, Choi S, Kim H. Development and validation of an instrument to measure undergraduate students' attitudes toward the ethics of artificial intelligence (AT-EAI) and analysis of its difference by gender and experience of AI education. Educ Inf Technol 2022;27(8):11635–67. https://doi.org/10.1007/s10639-022-11086-5 (Dordr).
[85] Järvelä S, Nguyen A, Hadwin A. Human and artificial intelligence collaboration for socially shared regulation in learning. Br J Educ Technol 2023;54(5):1057–76. https://doi.org/10.1111/bjet.13325.
[86] Johnston B, Webber S. Information literacy in higher education: a review and case study. Stud High Educ 2003;28(3):335–52. https://doi.org/10.1080/03075070309295.
[87] Kandlhofer M, Steinbauer G, Hirschmugl-Gaisch S, Huber P. Artificial intelligence and computer science in education: from kindergarten to university. In: Proceedings of the 2016 IEEE frontiers in education conference (FIE). IEEE; 2016. p. 1–9. https://doi.org/10.1109/FIE.2016.7757570.
[88] Kasneci E, Sessler K, Küchemann S, Bannert M, Dementieva D, Fischer F, Gasser U, Groh G, Günnemann S, Hüllermeier E, Krusche S, Kutyniok G, Michaeli T, Nerdel C, Pfeffer J, Poquet O, Sailer M, Schmidt A, Seidel T, Kasneci G. ChatGPT for good? On opportunities and challenges of large language models for education. Learn Individ Differ 2023;103:102274. https://doi.org/10.1016/j.lindif.2023.102274.
[89] Katz D. The functional approach to the study of attitudes. Public Opin Q 1960;24:163. https://doi.org/10.1086/266945. 2, Special Issue: Attitude Change.
[90] Khakurel J, Penzenstadler B, Porras J, Knutas A, Zhang W. The rise of artificial intelligence under the lens of sustainability. Technologies 2018;6(4):100. https://doi.org/10.3390/technologies6040100 (Basel).
[91] Kieslich K, Keller B, Starke C. Artificial intelligence ethics by design. Evaluating public perception on the importance of ethical design principles of artificial intelligence. Big Data Soc 2022;9(1). https://doi.org/10.1177/20539517221092956. 205395172210929.
[92] Kligyte V, Marcy RT, Waples EP, Sevier ST, Godfrey ES, Mumford MD, Hougen DF. Application of a sensemaking approach to ethics training in the physical sciences and engineering. Sci Eng Ethics 2008;14(2):251–78. https://doi.org/10.1007/s11948-007-9048-z.
[93] Kong SC, Cheung W, Zhang G. Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. Comput Educ Artif Intell 2021;2:100026. https://doi.org/10.1016/j.caeai.2021.100026.

[94] Krathwohl DR, Bloom BS, Masia BB. Taxonomy of educational objectives: the classification of educational goals. 1st ed. David McKay; 1964. reprintedTaxonomy of educational objectives: Handbook 2.
[95] Kruger J, Dunning D. Unskilled and unaware of it: how difficulties in recognizing one's own incompetence lead to inflated self-assessments. J Pers Soc Psychol 1999;77(6):1121–34. https://doi.org/10.1037//0022-3514.77.6.1121.
[96] Kuhail MA, Alturki N, Alramlawi S, Alhejori K. Interacting with educational chatbots: a systematic review. Educ Inf Technol 2023;28(1):973–1018. https://doi.org/10.1007/s10639-022-11177-3 (Dordr).
[97] Laupichler MC, Aster A, Haverkamp N, Raupach T. Development of the "Scale for the assessment of non-experts' AI literacy" – An exploratory factor analysis. Comput Hum Behav Rep 2023;12:100338. https://doi.org/10.1016/j.chbr.2023.100338.
[98] Laupichler MC, Aster A, Schirch J, Raupach T. Artificial intelligence literacy in higher and adult education: a scoping literature review. Comput Educ Artif Intell 2022;3:100101. https://doi.org/10.1016/j.caeai.2022.100101.
[99] Laupichler MC, Rother JF, Grunwald Kadow IC, Ahmadi S, Raupach T. Large language models in medical education: comparing ChatGPT- to human-generated exam questions. Acad Med J Assoc Am Med Coll 2023. https://doi.org/10.1097/ACM.0000000000005626. Advance online publication.
[100] Lévy-Leboyer C. La gestion des competences: une démarche essentielle pour la compétitivité des entreprises. Eyrolles; 2009. Nouvelle édition revue et augmentéeRessources humaines.
[101] Lievens F. Construct-driven SJTs: toward an agenda for future research. Int J Test 2017;17(3):269–76. https://doi.org/10.1080/15305058.2017.1309857.
[102] Lievens F, Schäpers P, Herde CN. Situational judgment tests: from low-fidelity simulations to alternative measures of personality and the person-situation interplay. A. Slaughter, P. D. Harms, S. J. Read, & D. Wood (Eds.). Measuring and modeling persons and situations. Academic Press; 2021. p. 285–311. https://doi.org/10.1016/B978-0-12-819200-9.00017-X.
[103] Lindvig K, Ulriksen L. Different, difficult, and local: a review of interdisciplinary teaching activities. Rev High Educ 2019;43(2):697–725. https://doi.org/10.1353/rhe.2019.0115.
[104] Livingstone S, van Couvering E. Information literacy. W. Donsbach (Ed.). The international encyclopedia of communication (1. publ). Wiley; 2008. https://doi.org/10.1002/9781405186407.wbieci021.
[105] Lohberger K, Braun E. Comparing learning opportunities of generic skills in higher education to the requirements of the labour market. Front Educ 2022;7:886307. https://doi.org/10.3389/feduc.2022.886307 (Lausanne)Article 886307.
[106] Lohse-Bossenz H, Bloss C, Dörfler T. Constructing multi-theory vignettes to measure the application of knowledge in ambivalent educational situations. Front Educ 2022;7. https://doi.org/10.3389/feduc.2022.996029 (Lausanne)Article 996029.
[107] Long D, Magerko B. What is AI literacy? Competencies and design considerations. In: Proceedings of the 2020 CHI conference on human factors in computing systems. ACM; 2020. p. 1–16. https://doi.org/10.1145/3313831.3376727.
[108] Long D, Teachey A, Magerko B. Family learning talk in AI literacy learning activities. In: Proceedings of the CHI conference on human factors in computing systems. ACM; 2022. p. 1–20. https://doi.org/10.1145/3491102.3502091.
[109] Loughlin C, Lygo-Baker S, Lindberg-Sand Å. Reclaiming constructive alignment. Eur J High Educ 2021;11(2):119–36. https://doi.org/10.1080/21568235.2020.1816197.
[110] Luan H, Geczy P, Lai H, Gobert J, Yang SJH, Ogata H, Baltes J, Guerra R, Li P, Tsai CC. Challenges and future directions of big data and artificial intelligence in education. Front Psychol 2020;11:580820. https://doi.org/10.3389/fpsyg.2020.580820.
[111] MacKenzie, Podsakoff. Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques. MIS Q 2011;35(2):293. https://doi.org/10.2307/23044045.
[112] MacTurk RH, Morgan GA. Advances in applied developmental psychology: Vol. 12. Mastery motivation: origins, conceptualizations, and applications. Ablex Pub; 1995.
[113] Mason RO. Four Ethical issues of the information age. J. Weckert (Ed.). International library of essays in public and professional ethics. Computer ethics. Routledge; 2017. https://doi.org/10.4324/9781315259697-8.
[114] McDaniel MA, Hartman NS, Whetzel DL, Grubb WL. Situational Judgement tests, response instructions, and validity: a meta-analysis. Pers Psychol 2007;60(1):63–91. https://doi.org/10.1111/j.1744-6570.2007.00065.x.
[115] Mikalef P, Gupta M. Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inf Manag 2021;58(3):103434. https://doi.org/10.1016/j.im.2021.103434.
[116] Mishra P, Warr M, Islam R. TPACK in the age of ChatGPT and generative AI. J Digit Learn Teach Educ 2023;39(4):235–51. https://doi.org/10.1080/21532974.2023.2247480.
[117] Mitchell, J., & Guile, D. (2022). Fusion skills and industry 5.0: conceptions and challenges. Chapters. https://ideas.repec.org/h/ito/pchaps/228513.html.
[118] Moore RL, Jiang S, Abramowitz B. What would the matrix do? a systematic review of K-12 AI learning contexts and learner-interface interactions. J Res Technol Educ 2023;55(1):7–20. https://doi.org/10.1080/15391523.2022.2148785.
[119] Motowidlo SJ, Dunnette MD, Carter GW. An alternative selection procedure: the low-fidelity simulation. J Appl Psychol 1990;75(6):640–7.
[120] Motowidlo SJ, Hooper AC, Jackson HL. Implicit policies about relations between personality traits and behavioral effectiveness in situational judgment items. J Appl Psychol 2006;91(4):749–61. https://doi.org/10.1037/0021-9010.91.4.749.
[121] Mousavi Baigi SF, Sarbaz M, Ghaddaripouri K, Ghaddaripouri M, Mousavi AS, Kimiafar K. Attitudes, knowledge, and skills towards artificial intelligence among healthcare students: a systematic review. Health Sci Rep 2023;6(3):e1138. https://doi.org/10.1002/hsr2.1138.
[122] Murphy, M., Hawwash, K., Vigild, M., & Fouger, X. (2016). *Position paper on engineering skills: developing graduate engineering skills.* European Society for Engineering Education. https://www.sefi.be/publication/position-paper-on-engineering-skills/.
[123] Nagel MT, Zlatkin-Troitschanskaia O, Fischer J. Validation of newly developed tasks for the assessment of generic Critical Online Reasoning (COR) of university students and graduates. Front Educ 2022;7. https://doi.org/10.3389/feduc.2022.914857 (Lausanne)Article 914857, 914857.
[124] Navigli R, Conia S, Ross B. Biases in large language models: origins, inventory, and discussion. J Data Inf Qual 2023;15(2):1–21. https://doi.org/10.1145/3597307.
[125] Nazaretsky T, Cukurova M, Ariely M, Alexandron G. Confirmation bias and trust: human factors that influence teachers' attitudes towards AI-based educational technology. In: Proceedings of the AI for blended-learning: empowering teachers in real classrooms co-located with 16th European conference on technology enhanced learning (ECTEL 2021); 2021. https://discovery.ucl.ac.uk/id/eprint/10141423/.
[126] Newberry B. The dilemma of ethics in engineering education. Sci Eng Ethics 2004;10(2):343–51. https://doi.org/10.1007/s11948-004-0030-8.
[127] Ng DTK, Leung JKL, Chu SKW, Qiao MS. Conceptualizing AI literacy: an exploratory review. Comput Educ Artif Intell 2021;2:100041. https://doi.org/10.1016/j.caeai.2021.100041.
[128] Ng DTK, Leung JKL, Su J, Ng RCW, Chu SKW. Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. Educ Technol Res Dev ETRD 2023;71(1):137–61. https://doi.org/10.1007/s11423-023-10203-6.
[129] Ng DTK, Wu W, Leung JKL, Chiu TKF, Chu SKW. Design and validation of the AI literacy questionnaire: the affective, behavioural, cognitive and ethical approach. Br J Educ Technol 2023. https://doi.org/10.1111/bjet.13411. Article bjet.13411. Advance online publication.
[130] Ng W. Can we teach digital natives digital literacy? Comput Educ 2012;59(3):1065–78. https://doi.org/10.1016/j.compedu.2012.04.016.
[131] Nguyen NT, Biderman MD, McDaniel MA. Effects of response instructions on faking a situational judgment test. Int J Sel Assess 2005;13(4):250–60. https://doi.org/10.1111/j.1468-2389.2005.00322.x.
[132] Nti IK, Adekoya AF, Weyori BA, Nyarko-Boateng O. Applications of artificial intelligence in engineering and manufacturing: a systematic review. J Intell Manuf 2022;33(6):1581–601. https://doi.org/10.1007/s10845-021-01771-6.
[133] Pereira V, Hadjielias E, Christofi M, Vrontis D. A systematic literature review on the impact of artificial intelligence on workplace outcomes: a multi-process perspective. Hum Resour Manag Rev 2023;33(1):100857. https://doi.org/10.1016/j.hrmr.2021.100857.
[134] Pinski M, Benlian A. Ai literacy - towards measuring human competency in artificial intelligence. T. X. Bui (Ed.). In: Proceedings of the 56th annual hawaii international conference on system sciences: january 3-6, 2023. Department of IT Management Shidler College of Business University of Hawaii; 2023. https://hdl.handle.net/10125/102649.
[135] Pinski M, Haas M, Franz A. AiLingo – a design science approach to advancing non-expert adults' AI literacy. In: Proceedings of the ICIS 2023; 2023. https://aisel.aisnet.org/icis2023/learnandiscurricula/learnandiscurricula/10.
[136] Pinto dos Santos D, Giese D, Brodehl S, Chon SH, Staab W, Kleinert R, Maintz D, Baeßler B. Medical students' attitude towards artificial intelligence: a multicentre survey. Eur Radiol 2019;29(4):1640–6. https://doi.org/10.1007/s00330-018-5601-1.
[137] Ployhart RE, Ehrhart MG. Be careful what you ask for: effects of response instructions on the construct validity and reliability of situational judgment tests. Int J Sel Assess 2003;11(1):1–16. https://doi.org/10.1111/1468-2389.00222.
[138] Prem E. From ethical AI frameworks to tools: a review of approaches. AI Ethics 2023;3(3):699–716. https://doi.org/10.1007/s43681-023-00258-9.
[139] Prentice R. Teaching behavioral ethics. J Legal Stud Educ 2014;31(2):325–65. https://doi.org/10.1111/jlse.12018.
[140] Raji ID, Scheuerman MK, Amironesei R. You can't sit with us. In: Proceedings of the 2021 ACM conference on fairness, accountability, and transparency. ACM; 2021. p. 515–25. https://doi.org/10.1145/3442188.3445914.
[141] Rajnai Z, Kocsis I. Assessing industry 4.0 readiness of enterprises. In: Proceedings of the 2018 IEEE 16th world symposium on applied machine intelligence and informatics (SAMI 2018). IEEE; 2018. p. 225–30. https://doi.org/10.1109/SAMI.2018.8324844. 7-10 February 2018.
[142] Rehm M, Bölsterli K. Entwicklung von unterrichtsvignetten. D. Krüger, I. Parchmann, & H. Schecker (Eds.). Methoden in der naturwissenschaftsdidaktischen forschung. Berlin Heidelberg: Springer; 2014. p. 213–25. https://doi.org/10.1007/978-3-642-37827-0_18.
[143] Rest JR, Narvaez D, Thoma SJ, Bebeau MJ. DIT2: devising and testing a revised instrument of moral judgment. J Educ Psychol 1999;91(4):644–59. https://doi.org/10.1037/0022-0663.91.4.644.
[144] Salazar-Gomez AF, Bagiati A, Minicucci N, Kennedy KD, Du X, Breazeal C. Designing and implementing an AI education program for learners with diverse background at scale. In: Proceedings of the 2022 IEEE frontiers in education conference (FIE). IEEE; 2022. p. 1–8. https://doi.org/10.1109/FIE56618.2022.9962632.

[145] Sanusi IT, Ayanwale MA, Tolorunleke AE. Investigating pre-service teachers' artificial intelligence perception from the perspective of planned behavior theory. Compu Educ Artif Intell 2024;6:100202. https://doi.org/10.1016/j.caeai.2024.100202.
[146] Sanusi IT, Olaleye SA, Oyelere SS, Dixon RA. Investigating learners' competencies for artificial intelligence education in an African K-12 setting. Comput Educ Open 2022;3:100083. https://doi.org/10.1016/j.caeo.2022.100083.
[147] Sanusi IT, Oyelere SS, Vartiainen H, Suhonen J, Tukiainen M. A systematic review of teaching and learning machine learning in K-12 education. Educ Inf Technol 2023;28(5):5967–97. https://doi.org/10.1007/s10639-022-11416-7 (Dordr).
[148] Schäpers P, Mussel P, Lievens F, König CJ, Freudenstein JP, Krumm S. The role of situations in situational judgment tests: effects on construct saturation, predictive validity, and applicant perceptions. J Appl Psychol 2020;105(8):800–18. https://doi.org/10.1037/apl0000457.
[149] Schepman A, Rodway P. Initial validation of the general attitudes towards Artificial Intelligence Scale. Comput Hum Behav Rep 2020;1:100014. https://doi.org/10.1016/j.chbr.2020.100014.
[150] Schepman A, Rodway P. The general attitudes towards artificial intelligence scale (GAAIS): confirmatory validation and associations with personality, corporate distrust, and general trust. Int J Hum Comput Interact 2023;39(13):2724–41. https://doi.org/10.1080/10447318.2022.2085400.
[151] Schleiss J, Laupichler MC, Raupach T, Stober S. AI course design planning framework: developing domain-specific AI education courses. Educ Sci 2023;13(9):954. https://doi.org/10.3390/educsci13090954 (Basel).
[152] Schwarz N. Attitude construction: evaluation in context. Soc Cogn 2007;25(5):638–56. https://doi.org/10.1521/soco.2007.25.5.638.
[153] Segun ST. Critically engaging the ethics of AI for a global audience. Ethics Inf Technol 2021;23(2):99–105. https://doi.org/10.1007/s10676-020-09570-y.
[154] Senkbeil M, Ihme JM, Schöber C. Wie gut sind angehende und fortgeschrittene Studierende auf das leben und arbeiten in der digitalen welt vorbereitet? Ergebnisse eines standard setting-verfahrens zur beschreibung von ICT-bezogenen kompetenzniveaus. Z Erziehungswiss 2019;22(6):1359–84. https://doi.org/10.1007/s11618-019-00914-z.
[155] Shih PK, Lin CH, Wu LY, Yu CC. Learning ethics in AI—teaching non-engineering undergraduates through situated learning. Sustainability 2021;13(7):3718. https://doi.org/10.3390/su13073718.
[156] Shin D, Shim J. A systematic review on data mining for mathematics and science education. Int J Sci Math Educ 2021;19(4):639–59. https://doi.org/10.1007/s10763-020-10085-7.
[157] Sindermann C, Sha P, Zhou M, Wernicke J, Schmitt HS, Li M, Sariyska R, Stavrou M, Becker B, Montag C. Assessing the attitude towards artificial intelligence: introduction of a short measure in German, Chinese, and English Language. KI Künstl Intell 2021;35(1):109–18. https://doi.org/10.1007/s13218-020-00689-0.
[158] Sit C, Srinivasan R, Amlani A, Muthuswamy K, Azam A, Monzon L, Poon DS. Attitudes and perceptions of UK medical students towards artificial intelligence and radiology: a multicentre survey. Insights Imaging 2020;11(1):14. https://doi.org/10.1186/s13244-019-0830-7.
[159] Sophian C. Beyond competence: the significance of performance for conceptual development. Cogn Dev 1997;12(3):281–303. https://doi.org/10.1016/S0885-2014(97)90001-0.
[160] Spante M, Hashemi SS, Lundin M, Algers A. Digital competence and digital literacy in higher education research: systematic review of concept use. Cogent Educ 2018;5(1):1519143. https://doi.org/10.1080/2331186X.2018.1519143.
[161] Stemler SE, Sternberg RJ. Using situational judgment tests to measure practical intelligence. Situational judgment tests. Psychology Press; 2013. p. 107–31. https://doi.org/10.4324/9780203774878-7.
[162] Stolpe K, Hallström J. Artificial intelligence literacy for technology education. Comput Educ Open 2024;6:100159. https://doi.org/10.1016/j.caeo.2024.100159.
[163] Suh W, Ahn S. Development and validation of a scale measuring student attitudes toward artificial intelligence. Sage Open 2022;12(2). https://doi.org/10.1177/21582440221100463. 215824402211004.
[164] Swanson L, Stocking ML. A model and heuristic for solving very large item selection problems. Appl Psychol Meas 1993;17(2):151–66. https://doi.org/10.1177/014662169301700205.
[165] Touretzky D, Gardner-McCune C, Martin F, Seehorn D. Envisioning AI for K-12: what should every child know about AI?. In: Proceedings of the AAAI conference on artificial intelligence. 33; 2019. p. 9795–9. https://doi.org/10.1609/aaai.v33i01.33019795.
[166] Tricot A, Sweller J. Domain-specific knowledge and why teaching generic skills does not work. Educ Psychol Rev 2014;26(2):265–83. https://doi.org/10.1007/s10648-013-9243-1.
[167] Tully, S., Longoni, C., & Appel, G. (2023). Knowledge of artificial intelligence predicts lower AI receptivity. 10.31234/osf.io/t9u8g.
[168] van Harreveld F, Nohlen HU, Schneider IK. The ABC of ambivalence. J. M. Olson & M. P. Zanna (Eds.). Advances in experimental social psychology, 52. Academic Press; 2015. p. 285–324. https://doi.org/10.1016/bs.aesp.2015.01.002.
[169] Vazhayil A, Shetty R, Bhavani RR, Akshay N. Focusing on teacher education to introduce AI in schools: perspectives and illustrative findings. In: Proceedings of the 2019 IEEE tenth international conference on technology for education (T4E). IEEE; 2019. p. 71–7. https://doi.org/10.1109/T4E.2019.00021.
[170] Verghese A, Shah NH, Harrington RA. What this computer needs is a physician: humanism and artificial intelligence. JAMA 2018;319(1):19–20. https://doi.org/10.1001/jama.2017.19198.
[171] Vuorikari, R., Kluzer, S., & Punie, Y. (2022). DigComp 2.2: the digital competence framework for citizens - with new examples of knowledge, skills and attitudes. 1018-5593. Advance online publication. 10.2760/490274.
[172] Walden S, Direito I, Berhan L, Clavero S, Galligan Y, Jolly A. ASEE & SEFI joint statement on diversity, equity, and inclusion: a call and pledge for action. American Society for Engineering Education; 2020. https://diversity.asee.org/wp-content/uploads/2020/05/ASEE-SEFI_DEIStatement.pdf.
[173] Wang B, Rau PLP, Yuan T. Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. Behav & Inf Technol 2022;42(9):1324–37. https://doi.org/10.1080/0144929X.2022.2072768.
[174] Wang W, Siau K. Artificial intelligence, machine learning, automation, robotics, future of work and future of humanity. J Database Manag 2019;30(1):61–79. https://doi.org/10.4018/JDM.2019010104.
[175] Weber P, Pinski M, Baum L. Toward an objective measurement of AI literacy. In: Proceedings of the PACIS 2023; 2023. https://aisel.aisnet.org/pacis2023/60.
[176] Weinert FE. Concept of competence: a conceptual clarification. D. S. Rychen & L. H. Salganik (Ed.). Defining and selecting key competencies. Hogrefe & Huber Publishers; 2001. p. 45–65.
[177] Weinert FE. Leistungsmessungen in schulen. Beltz; 2002.
[178] Whetzel D, Sullivan T, McCloy R. Situational judgment tests: an overview of development practices and psychometric characteristics. Pers Assess and Decis 2020;6(1). https://doi.org/10.25035/pad.2020.01.001.
[179] White RW. Motivation reconsidered: the concept of competence. Psychol Rev 1959;66:297–333. https://doi.org/10.1037/h0040934.
[180] Wienrich C, Carolus A. Development of an instrument to measure conceptualizations and competencies about conversational agents on the example of smart speakers. Front Comput Sci 2021;3:685277. https://doi.org/10.3389/fcomp.2021.685277. Article 685277.
[181] Winter SJM, Chudoba K, Gutek BA. Attitudes toward computers: when do they predict computer use? Inf Manag 1998;34(5):275–84. https://doi.org/10.1016/s0378-7206(98)00065-2.
[182] Winterton J, Turnbow T. What is competence? Theory, policy and practice. T. Dundon & A. Wilkinson (Eds.). Case studies in work, employment and human resource management. Edward Elgar Publishing; 2020. p. 123–8. https://doi.org/10.4337/9781788975599.00028.
[183] Wittig A. Implementing problem based learning through engineers without borders student projects. Adv Eng Educ 2013;3(4):1–20. https://advances.asee.org/publication/implementing-problem-based-learning-through-engineers-without-borders-student-projects/.
[184] Wolff A, Gooch D, Cavero Montaner JJ, Rashid U, Kortuem G. Creating an understanding of data literacy for a data-driven society. J Community Inform 2016;12(3). https://doi.org/10.15353/joci.v12i3.3275.
[185] Wong SC. Competency definitions, development and assessment: a brief review. Int J Acad Res Progress Educ Dev 2020;9(3):95–114. https://hrmars.com/index.php/IJARPED/article/view/8223/Competency-Definitions-Development-and-Assessment-A-Brief-Review.
[186] Xu JJ, Babaian T. Artificial intelligence in business curriculum: the pedagogy and learning outcomes. Int J Manag Educ 2021;19(3):100550. https://doi.org/10.1016/j.ijme.2021.100550.
[187] Younis HA, Eisa TAE, Nasser M, Sahib TM, Noor AA, Alyasiri OM, Salisu S, Hayder IM, Younis HA. A systematic review and meta-analysis of artificial intelligence tools in medicine and healthcare: applications, considerations, limitations, motivation and challenges. Diagnostics 2024;14(1):109. https://doi.org/10.3390/diagnostics14010109.
[188] Yu A, Douglas JA. IRT models for learning with item-specific learning parameters. J Educ Behav Stat 2023;48(6):866–88. https://doi.org/10.3102/10769986231193096.
[189] Zawacki-Richter O, Marín VI, Bond M, Gouverneur F. Systematic review of research on artificial intelligence applications in higher education – where are the educators? Int J Educ Technol High Educ 2019;16(1):1–27. https://doi.org/10.1186/s41239-019-0171-0.
[190] Zlatkin-Troitschanskaia O, Brückner S, Nagel MT, Bültmann AK, Fischer J, Schmidt S, Molerov D. Performance Assessment and digital training framework for young professionals' generic and domain-specific online reasoning in law, medicine, and teacher practice. J Supranatl Polic Educ JoSPoE 2021;(13):9–36. https://doi.org/10.15366/jospoe2021.13.001.
[191] Zlatkin-Troitschanskaia O, Pant HA, Greiff S. Assessing generic and domain-specific academic competencies in higher education. Z Pädagog Psychol 2019;33(2):91–3. https://doi.org/10.1024/1010-0652/a000236.