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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

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ABSTRACT

Valid measurement of AI literacy is important for the selection of personnel, identification of shortages in skill and knowledge, and evaluation of AI literacy interventions. A questionnaire is missing that is deeply grounded in the existing literature on AI literacy, is modularly applicable depending on the goals, and includes further psychological competencies in addition to the typical facets of AIL. This paper presents the development and validation of a questionnaire considering the desiderata described above. We derived items to represent different facets of AI literacy and psychological competencies, such as problem-solving, learning, and emotion regulation in regard to AI. We collected data from 300 German-speaking adults to confirm the factorial structure. The result is the Meta AI Literacy Scale (MAILS) for AI literacy with the facets Use & apply AI, Understand AI, Detect AI, and AI Ethics and the ability to Create AI as a separate construct, and AI Self-efficacy in learning and problem-solving and AI Self-management (i.e., AI persuasion literacy and emotion regulation). This study contributes to the research on AI literacy by providing a measurement instrument relying on profound competency models. Psychological competencies are included particularly important in the context of pervasive change through AI systems.

1. Introduction

It is an undeniable fact that Artificial Intelligence (AI) is coming into our daily lives. Interaction with AI or AI systems will become increasingly common for work or entertainment. Worldwide, about one-third of all companies used AI in 2022 which is an increase by four points compared to 2021.42% have not yet started using AI but explored the topic of AI in 2022 (IBM, 2022). The demand for individuals skilled in AI has steadily increased since 2014 compared to 2022, as the AI Adoption Index 2023 shows for North American, European, and other Western countries. For example, the number of AI-related job postings has increased on average from just above 0.50% in 2014 to 2.05% in 2022 in the United States (Maslej et al., 2023). In parallel, more AI-based technologies are being developed, as the average annual growth rate of filed AI patents is 76.6% between 2015 and 2021 (Zhang, Maslej, et al., 2022). The broad spectrum of AI brings with it challenges for understanding AI, as the underlying systems or capabilities of AI are complex and challenging to grasp (Wienrich & Latoschik, 2021). To find one's way in an AI-influenced world and to be able to act in a self-determined manner and participate in future developments, not only experts but also average users need an understanding of what AI is, what it can do, and how they can benefit (Carolus et al., 2022; Wienrich, Carolus, Markus, & Augustin, 2022). Just as computer skills became more important a few years ago, AI skills are becoming more relevant today. This set of skills includes using, applying, or interacting with AI and is commonly referred to as "AI literacy" (Long & Magerko, 2020). Individuals with high AI literacy will likely flourish in a working environment rich with AI, while individuals with low AI literacy will have

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problems when required to interact with AI. As automation and collaboration with AI will occur in many jobs (Frey & Osborne, 2017), an individual's current level of AI literacy might predict if they can adapt to new technologies and if implementing AI-reliant workflows will be successful. It is essential to develop suitable means to measure the AI literacy of individuals who are required to work with AI.

A reliable and valid measurement instrument for AI literacy is essential for selecting suitable personnel, identifying shortages in skills and knowledge that can be addressed, and evaluating interventions that focus on improving AI literacy. Specific tests and questionnaires were developed to measure AI literacy in educational settings where efforts are made to implement AI literacy into school curricula and develop educational approaches for increasing AI literacy (Dai et al., 2020; Kandlhofer et al., 2016; Rodríguez-García, Moreno-León, Román-González, & Robles, 2021; Wan et al., 2020a; Williams et al., 2019). Besides, there are few ways to measure AI literacy, and many scales are bound to specific contexts (e.g., useable only in an educational or medical setting) or need to be validated (Karaca et al., 2021; Wienrich & Carolus, 2021). Moreover, no measurement instrument takes into account psychological meta-competencies (Wienrich, Carolus, Markus, & Augustin, 2022). However, these are particularly important in work and adult education since the introduction of AI systems is often accompanied by general change processes that must be mastered constructively.

The goal of the present paper is to provide a measurement instrument that deals with the desiderata of current instruments and is modular in addition. In the context of this article, a modular measurement instrument is understood to be an instrument that consists of various components that can be used separately from one another. The present paper addresses these research gaps by presenting an empirical study on the systematic development and factorial validation of an AI literacy scale that meets psychometric requirements, is cross-contextual applicable, is embedded in the current literature on AI literacy, and considers psychological meta-competencies.

2. Theoretical background

Originally, "literacy" referred to the basic knowledge to read and write. More modern definitions apply a more general understanding of literacy as the "ability to identify, understand, interpret, create, communicate and compute, using printed and written materials associated with varying contexts" (for Statistics, nd). This, thus, involves not only basic skills of reading and writing but also more complex thought processes of comprehension, interpretation, and creation. In recent years, the term literacy has been used for a broader array of competencies regarding other domains (e.g., finance, health, or science). Most subtypes of literacy, however, focus on information technology (e.g., digital literacy, media literacy, information literacy, technology literacy, information technology literacy, social media literacy (Polanco-Levicán & Salvo-Garrido, 2022), digital interaction literacy (Carolus et al., 2022)).

AI literacy definitions differ in the exact number and configuration of competencies. There are many different conceptualizations and definitions of AI literacy: Ng and colleagues, in their review on AI literacy conceptualizations in education, postulate that these can be organized into four concepts: Know & understand AI, Use & apply AI, Evaluate & create AI, and AI ethics (Ng et al., 2021). They assume that AI literacy is given if an individual knows the basic functions of AI and can use AI applications, can apply AI knowledge in different scenarios, can evaluate, appraise, predict, and design AI applications, and can make ethical considerations. Most conceptualizations of AI literacy consider users as AI literate even if they do not have the in-depth technical knowledge and cannot develop or create AI. For example, Long & Magerko 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" (Long & Magerko, 2020). Cetindamar et al. (2022) define AI literacy as "a bundle of four core capabilities", namely *technology-related*, *work-related*, *human-machine-related*, and *learning-related* capabilities. They argue that technological capabilities will be necessary to understand and use AI, as it is based on technology. However, they limit these capabilities to the use of tools and data literacy and do not include in-depth programming skills to be part of AI literacy. Zhang, Lee, et al. (2022) developed a curriculum for middle schools to foster AI literacy with three components: *AI concepts* includes factual knowledge about AI and its concepts and technical details. *Ethical and societal implications* consists of the ability to understand the consequences of using AI for society, and *AI Career Future* concerns the impact of AI on future careers. However, in-depth technical knowledge about the creation of AI is not included. For their measurement instrument on AI literacy, Wang and colleagues define AI literacy to have the components *awareness*, *usage*, *evaluation*, and *ethics* but do not include the ability to develop AI applications as part of their conceptualization (Wang et al., 2022).

Bloom's taxonomy of educational objectives (Bloom, 1956) is also highly relevant to the definition of AI literacy and to the development of AI literacy scales. The taxonomy includes different levels of educational goals, such as the ability to remember terms and concepts (i.e., Remember) or more complex operations, like the ability to analyze complex matters. Even though it was not developed to function as a guideline for the construction of literacy conceptualizations or measurement scales, as Ng et al. (2021) conclude, most conceptualizations of AI literacy parallel Bloom's taxonomy regarding their general configuration of skills (Fig. 1). Since this taxonomy is the basis for numerous competence formulations in schools and universities, the present paper also relates to it by considering it a foundation for many AI literacy conceptualizations and scales.

There is one central point in which we differ from Bloom's taxonomy in our understanding of AI literacy. We do not expect all components of AI literacy to be ordered in a strict hierarchical sense. Instead, we assume that they are loosely connected. For example, it is possible to be able to create and develop AI without being able to make ethical considerations and evaluate the advantages and disadvantages of the use of AI.

2.1. Measuring AI literacy

Several scales have been developed to measure AI literacy so far. As many articles about AI literacy stem from an educational context, many measurement instruments were developed for the evaluation of a specific intervention. Often, teaching success is measured with single-choice or open-ended knowledge tests (e.g., Ali et al., 2019; Kandlhofer et al., 2016; Ng et al., 2022; Rodríguez-García et al., 2021; Wan et al., 2020b; Williams et al., 2019; Zhang, Lee, et al., 2022). The advantage of these tests is the apparently higher quality of measurement, which is only given to a limited extent with open answers, which are subject to personal opinions. An additional disadvantage of these tests is that they often remain close to the content of the intervention to be evaluated or to the content of the lesson. Other researchers in an educational context resort to self-assessments (e.g., Chai et al., 2020, 2021; Dai et al., 2020; Kim et al., 2021; Kim & Lee, 2022), which are easier to carry out and more objective as no interpretation of answers is necessary. Some research tends to use both options in combination (Kandlhofer et al., 2016; Zhang, Lee, et al., 2022). What all instruments used in schools have in common is that their factorial structure was not examined in large samples. Most of these questionnaires and tests might be helpful in evaluating specific interventions. However, they are less suitable for the measurement of AI literacy in a broader spectrum of use cases for two reasons: First, they heavily depend on the specific knowledge of the tested intervention. For example, in order to assess AI literacy in general in work contexts, it should be possible to query general criteria, which can then be combined with context-specific aspects in a modular way. Second, a large proportion of these studies do not differentiate between different aspects of AI literacy. Especially for

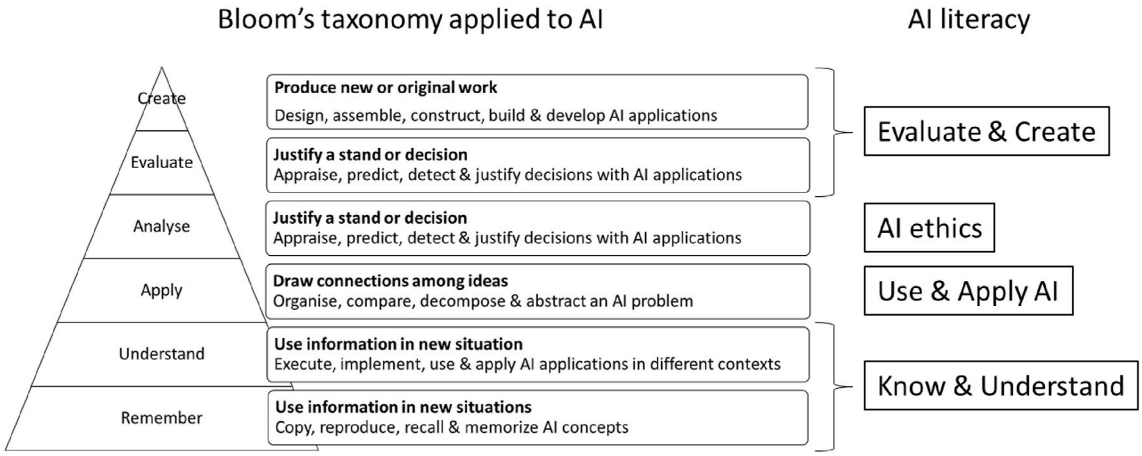

Fig. 1. Bloom's Taxonomy and AI literacy adapted from Ng et al. (2021).

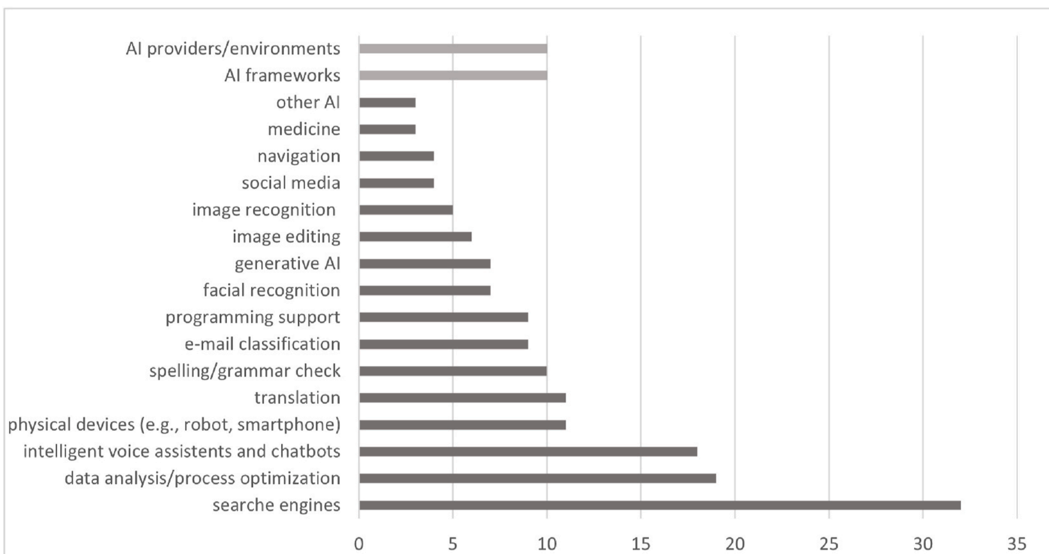

Fig. 2. AI used at work ($n = 178$) as reported by the participants ($N = 300$).

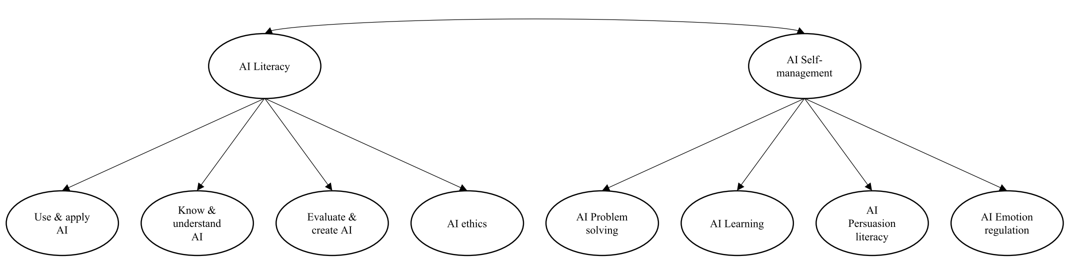

Fig. 3. Conceptual model for the confirmatory factor analysis.

its extensive use in science and practice, it is important to differentiate between distinct facets of AI literacy so that the questionnaire can be used economically and purposefully.

At the time of finalizing this paper, there were three published scales that could be used for a more general measurement of AI literacy and one collection of items to measure AI literacy. Karaca and colleagues created a scale to specifically measure the *AI Readiness* of medical students in healthcare through a self-report scale (Karaca et al., 2021). However, adapting the scale to different professional fields would be easily possible. The Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) was developed to measure medical students' readiness for using artificial intelligence in their work. Exploratory and confirmatory factor analysis showed a good fit for the 27-item scale, which tends to measure AI readiness in the four domains of "Cognition", "Ability", "Vision", and "Ethics". Another study on developing and validating a scale to measure AI literacy was published last year (Wang et al., 2022). The "artificial intelligence literacy scale" measures AI literacy with 12 items on the four dimensions of "Awareness", "Usage", "Evaluation", and "Ethics". Again, the identified dimensions were confirmed by factor analysis. However, Wang and colleagues draw heavily on existing literature on digital literacy to conceptualize AI literacy and develop their questionnaire. Both

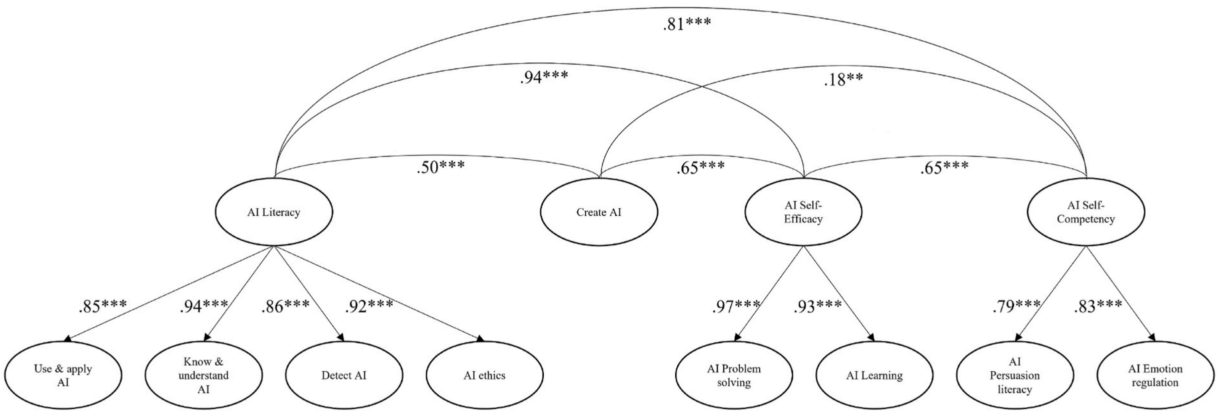

Fig. 4. Structural equation model of the modified confirmatory factor analysis. The items are omitted.

questionnaires do not consider the current theoretical advancements regarding the conceptualization of AI literacy (Ng et al., 2021). The third instrument was recently presented by Pinski and Benlian (2023). It is designed to measure the AI literacy of non-experts in the working context. Even though they refer to AI literacy conceptualizations (Long & Magerko, 2020; Ng et al., 2021), their conceptualization of AI literacy and the structure of the questionnaire are not based on these conceptualizations. Instead, they follow conceptualizations from the field of information systems (Schuetz et al., 2020) to guide their scale construction. Pinski and Benlian (2023) differentiate between explicit knowledge and tacit knowledge, which can be understood - and is measured in their instrument - as an experience rather than knowledge (i.e., "I have experience in interaction with different types of AI […]."). They also assume a "socio-technical" perspective in the development of their measurement instrument. However, this does not refer to similarities between human-AI interactions and human-human interaction. Instead, it is concerned with the knowledge of other human actors in the field of AI.

Laupichler et al. (2023) presented a collection of 38 items to measure AI literacy. They generated an initial set of items and asked experts in the field of AI education to refine the items following the Delphi method. Their item collection targets non-expert users of AI. Items are only loosely based on a recent AI literacy framework (Long & Magerko, 2020), which was used as an "implicit decision support tool". Also, no factor analysis was conducted to test the factorial structure and advance AI literacy conceptualizations.

The numerous current publications show that AI literacy is an important topic that is researched in very different and specialized ways. This results in measuring instruments that, on their own, produce a coherent structure but ignore essential aspects and thus have only a very limited scope of application. Established competence taxonomies like those of Bloom (1956) and Ng et al. (2021) are not consistently used as a theoretical basis for item formulation. Thus, the interpretation of latent factors also remains arbitrary. Therefore, we base our measurement instrument on the established competence taxonomy of Bloom (1956) and AI literacy conceptualization of Ng et al. (2021).

2.2. A psychological perspective on the measurement of AI literacy

When measuring human competencies such as AI literacy, several options (e.g., tests, observations of behavior, questionnaires) exist. Although tests tend to be more objective and observations tend to possess a higher validity, self-report questionnaires have a different advantage not despite but because they measure the self-perceived competence of an individual: According to the theory of planned behavior (Ajzen, 1985) or similar theories (e.g., adaptions to UTAUT2, Venkatesh et al., 2012; Alalwan et al., 2015; Lallmahomed et al., 2017; Gao et al., 2015), the perceived capabilities regarding a particular behavior (called perceived control or self-efficacy) are central to the intention of showing or changing a behavior. The theory of planned behavior (Ajzen, 1985) postulates that intentions and perceived behavioral control are most important to predict human voluntary behavior (such as the use of AI or managing AI-induced changes). Intentions, in turn, are centrally predicted by attitudes towards the behavior, the subjective norm (i.e., influences from the social environment), and perceived behavioral control. Thus, perceived behavioral control takes a unique role in that it influences behavior directly and indirectly (i.e., via intentions). Even though the theory of planned behavior is used mainly to predict change in health behavior and has been criticized (Sniehotta et al., 2014), recently, it has successfully been applied to predict the intention to use AI in different domains such as agriculture (Mohr & Kühl, 2021), and human resources (Alam et al., 2020), the intention to learn AI (Chai et al., 2021) or other related new technologies (Zaman et al., 2021). Outside the theory of the planned behavior framework, it was also shown that the subjective assessment of one's competencies is central to the intention to use AI (Kwak et al., 2022; Latikka et al., 2019). Consequently, according to an essential general psychological theory of intentional behavior, it is vital to measure perceived behavioral control for the target domain of AI usage in addition to other constructs, such as the attitude towards the usage of AI or social influences. From a psychological point of view, it is, thus, reasonable to resort to a self-report questionnaire to measure AI literacy.

However, the behavioral process does not end with the one-time formation of a behavioral intention (Gollwitzer, 1990). In the further course of the use of AI, the control of action and emotion processes is necessary for the successful long-term and sustainable use of AI (Gollwitzer, 1990). According to Bandura (1997), several sources are central to the formation of perceived behavioral control, which he calls self-efficacy. Individuals experience higher self-efficacy when they are successful themselves, when they see others being successful, when they experience no negative and high positive emotional arousal, and when they are supported by others. Especially new developments in the field of AI might hinder the long-term use of AI as they can have a negative effect on perceived behavioral control: Innovations might unsettle potential users, lead to failed behavior, and thus reduce perceived behavioral control. In addition, negative emotional states of arousal might occur, which can have further adverse effects on perceived behavioral control. We suggest that other psychological competencies are central to mitigating adverse effects on perceived behavioral control and, thus, the behavioral intention and actual use of AI. Learning, problem-solving, and emotion regulation might be needed to mitigate the adverse effects of innovations on perceived behavioral control. Especially learning and problem-solving regarding AI can enable the potential AI user to keep up with current developments in AI. Learning has been considered an essential part of or addition to AI literacy before (Carolus et al., 2022; Cetindamar et al., 2022; Dai et al., 2020). These competencies presumably lead to higher future use of AI by reducing failures leading to reduced perceived behavioral control. Additionally, emotion regulation helps to reduce harmful and increase positive emotional arousal (Carolus et al., 2022) and, by that, also increases perceived behavioral control. We argue that an instrument for measuring AI literacy to predict and prepare AI use in a professional context should, from a psychological point of view, primarily focus on the subjective assessment of one's competencies (i.e., behavioral control or self-efficacy). From the perspective of the theory of planned behavior (Ajzen, 1985), behavioral control takes on a central role. In addition to subjective competence, other competencies are also critical, especially to help predict and ensure the long-term use of AI. These include, in particular, the ability to learn, problem-solving skills, and emotion regulation to compensate for failures and resulting negative emotional arousal. In addition, we also consider the ability to recognize and prevent the influences of human-like voice-based AI systems (Carolus et al., 2022; Wienrich, Carolus, Roth-Isigkeit, & Hotho, 2022) as necessary. In the following, these competencies will be summarized under the term *AI Self-management*. We argue that AI Self-management is important to ensure the prolonged and sustainable use of AI and, thus, consider it to be an essential part of our measurement instrument.

2.3. Summary and present work

In summary, different conceptualizations of AI literacy exist where the main focus is on the domains of basic knowledge about AI, the use of AI, and ethical aspects of AI usage (Long & Magerko, 2020; Ng et al., 2021). Several measurement instruments already exist. However, some desiderata in the research on AI literacy measurement still need to be worked on.

1. In general, few measurement instruments with initial validations and theoretical foundations exist (Karaca et al., 2021; Wang et al., 2022), besides practically-oriented instruments often developed for a specific intervention study in an educational context.
2. Most instruments are not based on established theoretical competency modeling, making interpreting latent factors seem arbitrary.
3. Fewer researchers include the development of AI as a part of AI literacy or allude to initial psychological components, as described above (Carolus et al., 2022; Carolus & Wienrich, 2021; Wienrich, Carolus, Markus, & Augustin, 2022).
4. The assessment of related psychological constructs we call AI Self-management (i.e., emotion regulation, problem-solving, and learning in regard to AI) we deem vital information to support the long-term and sustainable use of AI at the workplace and beyond and has not been included in efforts to measure AI literacy.

With these desiderata in mind, this paper aims to meaningfully extend previous work on the conceptualization and measurement of AI literacy by developing a measurement instrument that:

1. Is deeply grounded in the existing literature on AI literacy,
2. Is modular (i.e., including different facets that can be used independently of each other) to be flexibly applicable in professional life depending on the goals,
3. Meets psychological psychometric requirements,
4. And includes further psychological competencies in addition to the classical facets of AI literacy.

The present study contributes to the research on the conceptualization and measurement of AI literacy by (a) presenting a newly developed measurement instrument and (b) testing the factorial structure. The measurement instrument differs from already existing instruments in several essential ways.

3. Empirical study

Empirical data were collected online from 300 individuals with a first language of German on the 3rd and 4th of November 2022 using the survey tool SoSci-Survey (Leiner, 2022). Participants were recruited using Prolific. co, an online platform that provides contacts to potential participants for online studies (Damer & Bradley, 2014). Participants were eligible for the study if they spoke German. We made no further requirements regarding socio-demographic data or prior experience with or knowledge of AI. The participants received short information about the purpose of the study before they could decide whether they wanted to start the study or not. They received compensation worth €3.38 for completion after their data was reviewed. 300 participants completed the study, two were rejected due to failed attention checks, 13 participants decided to return their submission, and three participants did not complete the study. Preliminary testing resulted in an average completion time of approximately 20 min. The average completion time was 16:05 min (SD = 5:46), amounting to an average reward of approximately €12.8/hour. All participants were asked to give informed consent prior to participation. In addition to the items we generated for AI literacy following the conceptualization by Ng and colleagues (Ng et al., 2021), the creation and development component of (Bloom, 1956) and AI Self-management, anthropomorphism tendency, attitudes towards AI, and the willingness to use technology and demographic information were assessed mainly using standardized instruments.

3.1. Sample

In the present sample, the average age was 32.13 years ($SD = 11.66$ years, ranging from 18 to 72 years). Most participants lived in Germany (77.00%) or Austria (7.00%). 145 participants considered themselves female (48.33%), while 152 participants identified as male (50.67%). 3 participants identified as diverse (1.00%). Participants were asked to indicate their experience with AI by rating three statements "I use artificial intelligence at work", "I use artificial intelligence at school/university", and "I use artificial intelligence in my everyday life" on an 11-point Likert scale (0 = "never or only very rarely" to 10 = "very often"). Almost one-fifth of the participants (19.67%) reported never using AI in their everyday lives, at school/university, or at work. The average scores (and standard deviation) were $M = 1.84$ (2.79) for work, $M = 1.21$ (2.31) for school/university, and $M = 3.73$ (3.03) for everyday life respectively showing rather low use of AI on the scale of 0 = "never or only very rarely" to 10 = "very often". Participants were also asked to report the AI they use at work (Fig. 2). In total, the participants reported the use of 158 AI-based systems. The scope ranged from the use of devices with AI, to the use of programs that include AI functions, to the autonomous implementation of machine learning processes. Ten AI frameworks and ten AI providers and environments (e.g., Amazon, Watson) were reported.

3.2. Measures

All measures were administered online via SoSci-Survey in German. Prior to participation, the participants were informed about the general purpose of the study and gave their informed consent.

3.2.1. AI literacy and AI self-management

After reviewing the literature on AI literacy described in the theoretical background, we generated 56 items for the self-assessments in different domains of AI literacy. We focused on the four superordinate domains described by Ng et al. Ng et al. (2021) 1, namely Know & understand AI, Use & apply AI, Evaluate & create AI, and AI ethics. The item construction was heavily guided by the conceptualization of Ng et al. as each item was developed to directly represent one of their domains of AI literacy. 15 Items were developed for Know & understand

AI, while 12 items were created for Use & apply AI. The original item pool we generated for Evaluate & create AI consisted of 15 items for Evaluate and 9 for Create AI. Lastly, 5 items were created for AI ethics. In addition to the items aiming at the assessment of the domains of AI literacy, we generated 12 items (three per construct) to measure additional constructs derived from the literature as presented above we deemed necessary for individuals working on and with AI. These constructs include (a) the ability to manage one's own emotions while interacting with AI, called Emotion regulation, (b) the ability to recognize if one's decisions are influenced by AI and to stop this influence (i.e. "AI persuasion literacy"), (c) the ability to solve problems encountered while working with AI (i.e., AI problem solving), and (d) the ability to keep up to date with current developments and inform oneself about new AI applications, called Learning. These abilities have in common that they describe self-management aspects: They include managing one's own emotions and decisions as well as the management of problem-solving and learning processes. In the first step, for each of the domains, items were generated by one researcher. Then, the items were discussed, rephrased, rejected, and finalized by our team of researchers from the areas of human-computer interaction and psychology. The 12 items on AI self-management and 56 items on AI literacy were administered first. Each item included a statement about a specific ability related to one of the domains of AI literacy or AI self-management (e.g., "I can develop new AI applications."). The participants were asked to rate their own abilities using an 11-point Likert scale (0–10). We decided to use this scale because it can easily be understood as the certainty of being able to show a behavior Bandura et al. (2006). There is no scale labeling to achieve an approximate metric scale level. The only additional information the participants receive is that a value of 0 means that the ability is hardly or not at all pronounced, whereas a value of 10 means that the ability is very well or almost perfectly pronounced.

3.2.2. *Attitude towards AI*

To measure attitude toward AI, we used our own German translation of the General Attitude towards Artificial Intelligence Scale (GAAIS) (Schepman & Rodway, 2020). The scale consists of 20 items that measure positive (e.g., "There are many beneficial applications of Artificial Intelligence") and negative (e.g., "I think Artificial Intelligence is dangerous") attitudes towards AI. Participants rate their attitude towards AI on a 5-point Likert scale with the anchors strongly "disagree"/"somewhat disagree"/"neutral"/"somewhat agree"/"strongly agree". In our sample, both subscales showed high internal consistencies ($\alpha = 0.88$ for positive and $\alpha = 0.82$ for negative attitude).

3.2.3. *Willingness to use technology*

The short scale for willingness to use technology (Neyer et al., 2012) measures the acceptance of technology (i.e., "I am curious about new technical developments."), the competence (i.e.," I usually find using modern technology to be a challenge.") and the perceived control (i.e.," Whether or not I succeed in using modern technology largely depends on me.") when using new technologies with four items per scale. Participants rate the items regarding their willingness to work with technology on a 5-point Likert scale (from 1 = "not true at all" to 5 = "completely true"). The items for "competence" were recoded so that a high value indicates a high perceived competence in line with the other two scales. All three scales showed good internal consistencies (all $\alpha > 0.81$). We are aware that the use of 5-point Likert scales is often discouraged (e.g., Dawes, 2008; van Beuningen et al., 2014). Although being aware of the disadvantages of 5-point Likert scales we decided to stick as close to the original scales as possible. Descriptive information for the attitude towards AI and willingness to use technology can be seen in Table 1.

3.3. *Results*

To test the factorial structure of our measurement instrument, we calculated a confirmatory factor analysis with the package lavaan for R (Rosseel, 2012) (version 0.6–12) and used robust Satorra-Bentler estimations. In the first step, we included all items on AI literacy and AI self-management. Based on the conceptual derivation/structure of the items (3), we tested if the items loaded on the factor they were developed in reference to. The lower level factors Know & understand AI, Use & apply AI, Evaluate & create AI, and AI ethics were expected to load on the second-level factor called AI literacy. The factors AI Problem solving, AI Learning, AI Persuasion literacy, and AI Emotion regulation were expected to load on the second-level factor we called AI Self-management; Fig. 3).

Because of an insufficient model fit, in the second step, we made the following changes: We removed 34 items that showed low factor loadings. In order to guarantee that the questionnaire still covers all the domains of AI literacy, we ensured that only items were removed that doubled in content with the remaining items. Three items from the factor Know & understand AI were moved to a separate factor named Detect AI. The model was changed so that the level one factor, Create AI, does not load on the level two factor AI literacy. Lastly, the level two factor AI Self-management was split into the factors AI Self-efficacy (including AI Learning and AI Problem solving) and AI Self-competency (including AI Persuasion literacy and AI Emotion regulation. We re-run the confirmatory factor analysis with the changes. The final questionnaire can be seen in the appendix. The model fit for the modified model was good. Although the χ^2-test became significant ($\chi^2(513) = 886.87$, $p < 0.001$), the other model fit indices showed a good model fit (CFI = 0.926, RMSEA = 0.057, 95 %-CI [0.051, 0.063], SRMR = 0.079). CFI > 0.9 and RMSEA < 0.08 indicate an acceptable model fit, while an SRMR > indicates no good fit (Kline, 2015).

All items loaded significantly on their respective factor (all $p < 0.001$), and all level one factors loaded significantly on their respective level two factor (all $p < 0.001$). All level two factors were significantly correlated (all $p < 0.01$). Interestingly, AI Self-efficacy and AI Self-competency showed very high correlations with AI literacy, whereas they were still highly correlated with each other, but to a lesser extent. The result of the confirmatory factor analysis is a measurement model for 34 manifest items on AI literacy and related psychological competencies (Fig. 4). A total of 18 items load on the level-one factors loading on the level-two factor AI literacy: Six items each load on the latent dimensions Use & Apply AI (Cronbach's $\alpha = 0.93$) and Know & Understand AI (Cronbach's $\alpha = 0.87$). Three items each load on the latent dimensions Detect AI (Cronbach's $\alpha = 0.77$) and AI Ethics (Cronbach's $\alpha = 75$). Four items directly load on the second-level latent dimension Create AI (Cronbach's $\alpha = 0.92$). Three items each load on the first-level latent dimensions AI Problem solving (Cronbach's $\alpha = 0.84$) and Learning (Cronbach's $\alpha = 0.84$) loading on the second-level latent dimension AI Self-Efficacy. For the second-level latent dimension AI Self-competency, three items load on the first-level latent dimensions of AI Persuasion literacy (Cronbach's $\alpha = 0.66$) and AI Emotion regulation (Cronbach's $\alpha = 0.71$). All second-level latent dimensions were significantly correlated with each other (Fig. 4).

In the third step, we additionally included the subscales for attitude towards AI and willingness to use technology as additional latent variables to the structural equation model. All items loaded significantly on

Table 1
Descriptive statistics for AI attitudes (positive and negative) and willingness to use new technology (acceptance, competence, control).

		mean	sd	median	min	max
AI attitude	Positive attitude	3.60	0.57	3.67	1.50	4.92
	Negative attitude	2.74	0.67	2.75	1.13	4.50
Willingness to use technology	Acceptance	3.56	0.94	3.75	1.00	5.00
	Competence	4.83	0.82	4.29	1.00	5.00
	Control	3.85	0.68	4.00	1.75	5.00

their respective scale (all $p < .001$). The correlations of the latent variables can be seen in Table 2. The model showed an acceptable model fit ($\chi^2(2035) = 3004.35$, $p < 0.001$, CFI = 0.900, RMSEA = 0.043, 95 %-CI [0.039, 0.047], SRMR = 0.069). A CFI > 0.9 and an RMSEA < 0.08 indicate an acceptable fit, while an SRMR > 0.05 indicates no good fit (Kline, 2015).

Self-assessed competence in the use of new technologies correlated positively only with Create AI. It did not correlate with AI Self-efficacy and only negatively with AI literacy and AI Self-competency. All AI competencies correlated positively with the perceived control over new technology and acceptance of new technology except Create AI, which did not correlate with perceived control over new technology. A positive attitude towards AI was positively correlated with all AI competencies. A negative attitude was negatively correlated to AI literacy and AI Self-competency but was not correlated to Create AI and AI Self-efficacy.

4. Discussion

The aim of this paper was to develop and validate a questionnaire to assess AI literacy that targets several desiderata of current measurement instruments. In contrast to existing questionnaires, first, the questionnaire should be deeply grounded in the existing literature on AI literacy. Second, the questionnaire should be modular (i.e., including different facets that can be used independently of each other) to be flexibly applicable in professional life, depending on the goals and use cases. Third, the questionnaire should meet psychological requirements, and, fourth, it should include further psychological competencies in addition to the classical facets of AI literacy. For this purpose, the data of 300 German-speaking adults were analyzed with confirmatory factor analyses. The analyses resulted in a questionnaire consisting of 34 items to measure AI literacy and psychological competencies necessary for the sustainable use of AI literacy. Items were generated in direct reference to established conceptualizations of competencies (Bloom, 1956) and AI literacy (Ng et al., 2021). The measurement instrument can be used to measure AI literacy and additional psychological competencies independent of the context. The MAILS will have an impact on different fields as its application can help select suitable personnel, identify shortages in skills and knowledge that can be addressed, and evaluate interventions.

Instead of the eight factors (four derived from the literature, Ng et al., 2021) and four to measure specific psychological aspects we deemed essential) that loaded on 2 s-level factors (i.e., AI literacy and AI Self-management), we found the facets Use & Apply AI, Know & understand AI, Detect AI, and AI Ethics which loaded on a second-level factor called AI literacy. Nearly all scales of the questionnaire showed acceptable (Cronbach's $\alpha > .7$), good (Cronbach's $\alpha > 0.8$), or high (Cronbach's $\alpha > 0.9$) values for Cronbach's alpha supporting the composite reliability of each scale. Only the latent dimensions of AI Persuasion literacy showed a slightly low value (Cronbach's $\alpha = 0.66$). Interestingly, the facet Create AI did not load on AI literacy and was only correlated to it with a $r = 0.5$. This result from our measurement model can be seen as support for the conceptualizations which do not include the creation of AI as a part (or dimension) of AI literacy. Instead, our research suggests that Create AI should be operationalized as a separate skill that is related to, but not an inherent part of, AI literacy. This is in line with most conceptualizations of AI literacy where the development of AI is not explicitly mentioned (Dai et al., 2020; Kong et al., 2021; Long & Magerko, 2020), however, is in conflict with the conceptualization by Ng et al. (2021). The structure found, where Create AI does not load on AI literacy but is correlated to it, covers this dichotomy well, and the dimension Create AI can be measured modularly along with AI literacy.

Concerning the domain AI literacy, we found further discrepancies between the first specified model and the final model. Interestingly, items for the evaluation of AI did not load on one factor with items on Create AI but loaded on the factor for Know & understand AI. It seems that the ability to evaluate AI is more closely related to the general knowledge and understanding of AI than to the ability to develop AI. Presumably, according to the subjects' self-assessment, for the evaluation of AI systems, precise knowledge and understanding (i.e., Know & understand AI) are more important than the ability to actually develop AI. This fits in with the general picture that Create AI is separate (Dai et al., 2020; Kong et al., 2021; Long & Magerko, 2020) and no part of AI literacy. Our findings, thus, partly contradict the conceptualization by Ng et al. (2021), who included Create AI as a component of their AI literacy conceptualization. Additionally, we found a common factor for the ability to detect AI similar to the dimensions "Awareness" (e.g., "I can distinguish between smart devices and non-smart devices.", Wang et al. (2022)). Possibly, recognizing AI does not seem to be necessarily tied to knowing and understanding AI, but also is an independent competence. This is in line with the conceptualization by Long and Magerko (2020), who included the ability to recognize AI in their framework. However, as expected, we found the other factors with the expected items to load on the second-level latent dimension called AI literacy.

In place of one domain called AI Self-management, which includes the factors AI Problem solving, AI Learning, AI Persuasion literacy, and AI Emotion regulation, we found 2 s-level latent domains we called AI Self-efficacy (including the factors AI Problem solving and AI Learning) and AI Self-competency (including AI Persuasion literacy and AI Emotion regulation). Possibly, problem-solving and learning are competencies that are primarily aimed at managing information and information processing, while persuasion literacy and emotion regulation also focus on the management of information, albeit with greater personal value (own decisions and emotions). We follow the opinion that these factors are important for the prolonged and sustainable use of AI tools (Carolus et al., 2022; Carolus & Wienrich, 2021; Cetindamar et al., 2022; Dai et al., 2020; Wienrich, Carolus, Markus, & Augustin, 2022). A clear correlation emerged between AI Self-efficacy and AI Self-competency, although the subordinate factors do not load on one common factor. It is possible that similar cognitive processes are necessary for the management of processes that are more concerned with the processing of information (AI Self-efficacy) or emotions and decisions (AI Self-competency), leading to a high correlation among both domains. However, enough uniqueness exists in both constructs. So

Table 2
Correlations from the structural equation model.

	2.	3.	4.	5.	6.	7.	8.	9.
1. AIL	0.49***	0.86***	0.93***	0.14*	0.20**	0.47***	−0.17*	0.47***
2. Create		0.24**	0.63***	−0.18*	−0.02	0.21***	0.10	0.14*
3. AISC			0.72***	0.24**	0.31***	0.36***	−0.27**	0.28**
4. AISE				0.06	0.17**	0.48***	−0.10	0.33***
5. Competence					0.41***	0.42***	−0.39***	0.22**
6. Control						0.46***	−0.27***	0.36***
7. Acceptance							−0.30***	0.00
8. Negative								−0.43***
9. Positive								

Note. * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$; AIL = AI literacy, AISC = AI self-competency, AISE = AI self-efficacy.

far, conceptual thinking existed to include such aspects (Carolus et al., 2022; Carolus & Wienrich, 2021; Cetindamar et al., 2022; Dai et al., 2020; Wienrich, Carolus, Markus, & Augustin, 2022), Wienrich, Carolus, Roth-Isigkeit, & Hotho, 2022ut no measurement tool yet. Our measurement instrument, therefore, provides new value and an essential contribution to existing considerations. This is the first step regarding the individual differences in such a general measuring instrument (Wienrich, Carolus, Roth-Isigkeit, & Hotho, 2022).

There are high correlations between the constructs of our questionnaire (i.e., AI literacy, AI Self-competency, Create AI, and AI Self-efficacy), but still enough differentiation that they can be understood as unique constructs. All second-level latent dimensions positively correlate with positive attitude toward AI. AI literacy and AI Self-competency negatively correlate to a negative attitude towards AI, while Create AI and AI Self-efficacy do not. Presumably, individuals with a higher positive attitude also deal with the topic more often and are, therefore, more competent. Similar is true for negative attitude (but only for some of the constructs), with lower negative attitude going hand in hand with higher literacy and self-competence. Possibly, individuals with lower negative attitude (i.e., less fear or anxiety) show higher values of AI literacy and AI Self-competency because they interact with AI more frequently. Alternatively, individuals with higher self-competency are better at regulating their emotions and attitudes (i.e., less fear or anxiety), leading to less negative attitude. In a similar way, the three dimensions of the willingness to use technology are positively related to most of the dimensions of our questionnaire. These correlative findings suggest that there are relations between competencies related to AI and attitudes towards AI as well as the willingness to use new technology. Individuals with higher positive attitudes, lower negative attitudes, and more willingness to use technology are more likely to consider themselves competent (Ajzen, 1985; Wienrich & Carolus, 2021; Wienrich, Carolus, Roth-Isigkeit, & Hotho, 2022). One reason may be that these individuals are also more likely to use AI and thus become more competent.

4.1. Limitations and future work

Several limitations need to be mentioned in regard to the empirical study presented in this paper. Our sample was collected online and is specific to German-speaking individuals who live in Germany or Austria. Also, it was not possible to use an already existing and validated instrument on AI literacy to validate our questionnaire, as would be the gold standard for scale development. Although other instruments exist, none have been validated with external criteria so far. Even though we chose confirmatory factor analysis to test our models, we made changes to the model, thus, it is necessary to consider our approach exploratory. It is, therefore, highly important to confirm the factorial structure we identified in an independent sample.

Future research should aim to test the factorial structure we identified in independent samples. The most critical next step, however, is the validation of our questionnaire. This could be done by either correlating our questionnaire results with results of tests, tasks, or the evaluations of individual AI literacy by an expert or by correlating it to a validated questionnaire that might be published in the future. Alternatively, other external criteria could be used: We could test if the instrument is capable of detecting expected group differences or finding change after interventions/in the course of professional studies. We are currently exploring available options to test the predictive validity and construct validity of the scale in samples of university students. For this purpose, it seems possible to ask students in AI and machine learning university courses to complete the scale and also report their grades in the respective course. Additionally, a comparison with the other existing instruments regarding their predictive validity (e.g., use them to predict the quality of future AI-related behavior) would be interesting to identify the worth of the additional scales we included. Also, testing the discriminant validity of the scale by comparing it with other constructs (e.g., intelligence, IT literacy, data literacy) might be highly relevant to prove the instrument's worth. A translation of the MAILS seems reasonable to measure AI literacy in different linguistic and cultural contexts. Additional effort is necessary to translate the questionnaire and validate it. Ensuring measurement invariance would be an important condition for using the MAILS cross-linguistically and culturally.

4.2. Conclusion

The current study aimed to develop and validate a questionnaire to measure AI literacy and include psychological competencies that might be helpful in predicting the prolonged and sustainable use of AI. We based our developed items on the existing literature on AI literacy and psychological competencies. Overall, we found the factors Use & Apply AI, Know & understand AI, and AI Ethics (Ng et al., 2021) with the addition of Detect AI. The factor Evaluate & Create AI was not found. While the items on the evaluation of AI loaded on Know & understand AI, the items on the creation of AI formed their own factor that cannot be seen as an inherent part of AI literacy. Instead of finding one superordinate factor for the psychological competencies related to AI, we found two (i.e., AI Self-efficacy and AI Self-competency). We mainly found positive relations for our questionnaires' dimensions with attitudes toward AI and willingness to use technology. Create AI is a notable special case in that its correlations to attitudes and willingness are comparatively low compared to the other dimensions of our scale. The developed scale will contribute to the current research on AI literacy and will facilitate the implementation of AI into working environments by providing a valid measurement for AI literacy and related psychological competencies that can be used by various practitioners and researchers. In addition, it has theoretical implications as it helps to get a better understanding of AI literacy. Further research will be needed to relate our measure to other valid measures of AI literacy and compare their predictive validity. The current study contributes to the existing research by providing a measurement instrument for AI literacy that is based on the current literature on AI literacy, includes important psychological constructs, and has a valid factorial structure. The instrument will be helpful for researchers, practitioners, and educators who plan to measure AI literacy and related constructs.

Declaration of competing interest

The authors have no competing interest to declare.

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Appendix A. Structure and all items of the Meta AI literacy Scale and sources that motivate each facet

AI literacy
Apply AI (Ng et al., 2022)
1. I can operate AI applications in everyday life.
2. I can use AI applications to make my everyday life easier.
3. I can use artificial intelligence meaningfully to achieve my everyday goals.
4. In everyday life, I can interact with AI in a way that makes my tasks easier.
5. In everyday life, I can work together gainfully with an artificial intelligence.
6. I can communicate gainfully with artificial intelligence in everyday life.
Understand AI (Ng et al., 2022)
7. I know the most important concepts of the topic ”artificial intelligence”.
8. I know definitions of artificial intelligence.
9. I can assess what the limitations and opportunities of using an AI are.
10. I can assess what advantages and disadvantages the use of an artificial intelligence entails.
11. I can think of new uses for AI.
12. I can imagine possible future uses of AI.
Detect AI (Long & Magerko, 2020; Wang et al., 2022)
13. I can tell ifI am dealing with an application based on artificial intelligence.
14. I can distinguish devices that use AI from devices that do not.
15. I can distinguish if I interact with an AI or a ”real human”.
AI Ethics (Ng et al., 2022)
16. I can weigh the consequences of using AI for society.
17. I can incorporate ethical considerations when deciding whether to use data provided by an AI.
18. I can analyze AI-based applications for their ethical implications.
Create AI (Ng et al., 2022)
19. I can design new AI applications.
20. I can program new applications in the field of ”artificial intelligence”.
21. I can develop new AI applications.
22. I can select useful tools (e.g., frameworks, programming languages) to program an AI.
AI Self-Efficacy
AI Problem solving (Ajzen, 1985)
23. I can rely on my skills in difficult situations when using AI.
24. I can handle most problems in dealing with artificial intelligence well on my own.
25. I can also usually solve strenuous and complicated tasks when working with artificial intelligence well.
Learning (Carolus et al., 2022; Cetindamar et al., 2022; Dai et al., 2020)
26. I can keep up with the latest innovations in AI applications.
27. Despite the rapid changes in the field of artificial intelligence, I can always keep up to date.
28. Although there are often new AI applications, I manage to always be ”up-to date”.
AI Self-Competency
AI Persuasion literacy (Carolus et al., 2022)
29. I don't let AI influence me in my everyday decisions.
30. I can prevent an AI from influencing me in my everyday decisions.
31. I realise if artificial intelligence is influencing me in my everyday decisions.
AI Emotion regulation (Carolus et al., 2022)
32. I keep control over feelings like frustration and anxiety while doing everyday things with AI.
33. I can handle it when everyday interactions with AI frustrate or frighten me.
34. I can control my euphoria that arises when I use artificial intelligence for everyday purposes.

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