Passlack, Nina; Hammerschmidt, Teresa; Posegga, Oliver

With Great Power Comes Great Responsibility : What Shapes AI Literacy for Responsible Interactions of Knowledge Workers With AI?

Date of secondary publication: 13.03.2026

Version of Record (Published Version), Article

Persistent identifier: urn:nbn:de:bvb:473-irb-114268x

Primary publication

Passlack, Nina; Hammerschmidt, Teresa; Posegga, Oliver (2026): With Great Power Comes Great Responsibility : What Shapes AI Literacy for Responsible Interactions of Knowledge Workers With AI?, in: Information systems frontiers : a journal of research and innovation, Dordrecht [u.a.]: Springer Science + Business Media B.V, Vol. 28, No. 1, pp. 11–46, doi: 10.1007/s10796-025-10648-5.

Information Systems Frontiers (2026) 28:11–46
https://doi.org/10.1007/s10796-025-10648-5

With Great Power Comes Great Responsibility: What Shapes AI Literacy for Responsible Interactions of Knowledge Workers With AI?

Nina Passlack[1] · Teresa Hammerschmidt[1] · Oliver Posegga[1]

Received: 4 October 2024 / Accepted: 27 August 2025 / Published online: 22 October 2025

Abstract
The growing autonomy and self-learning abilities of advanced technologies alter the dynamics of human-AI interaction, while also raising important ethical concerns. This study calls for rethinking AI literacy to encompass additional abilities necessary for responsible human-AI interaction. Beyond enhancing efficiency and performance, research on AI literacy must address unintended consequences and risks, and thus requires a digital responsibility perspective. Through interviews with different groups of knowledge workers, the study outlines factors that enable and influence knowledge workers to interact responsibly with AI technologies. Our research uncovers tensions concerning the concept of AI literacy that may challenge responsible human-AI interaction. These concern especially problems related to skill development and responsibility attribution. These problems emphasize the need for shared responsibilities and to ensure alignment between knowledge workers' abilities and their roles – what we call the "role-ability fit." We further offer recommendations to promote responsible human-AI interaction.

Keywords AI literacy · Human-AI interaction · AI knowledge · Responsibility

1 Introduction

Digital technologies based on artificial intelligence (AI) are widely used in knowledge workers' daily lives (Dwivedi et al., 2023); their growing power reminds us of the old adage that "with great power comes great responsibility." This growing power stems from AI's increased cognitive and self-learning abilities to generate knowledge (Berente et al., 2021), prepare decisions, and carry out tasks that were previously done by individuals (Rai et al., 2019), thus transforming aspects of contemporary society and business life (Constantinescu et al., 2021). The greater responsibility arises from the blurred lines of responsibilities when AI technologies operate (semi-)autonomously, and accountability for unintended consequences remains unclear (Giermindl et al., 2022; Matthias, 2004). A lack of the skills required for interacting with AI may lead to gaps between individuals who are and are not able to use AI technologies responsibly (Celik, 2023). It may also result in unintended consequences that create inequalities, such as the exclusion of marginalized groups of people (Alexopoulou et al., 2022; Celik, 2023).

To avoid such inequalities and mitigate potential negative or unintended consequences of human-AI interaction, we need to rethink the concept of AI literacy. First, individuals must acquire new abilities that will enable them to interact with AI responsibly (Rana et al., 2022). These include being able "to evaluate AI technologies critically; communicate and collaborate effectively with AI; and use AI as a tool" (Long & Magerko, 2020, p. 2). Current research refers to this as AI literacy (e.g., Ng et al., 2022; Pinski & Benlian, 2023), and some valuable conceptualizations of AI literacy exist (e.g., Cetindamar et al., 2022; Heyder & Posegga, 2021; Pinski & Benlian, 2023; Wang et al., 2022). Second, conceptualizations of AI literacy should take into account the various influencing factors that shape skill development and determine competency requirements. Building upon existing conceptualizations, our work aims to outline components that are critical to AI literacy for achieving *responsible* outcomes of human-AI interaction alongside those that are essential for achieving *efficient* outcomes, such as increased performance and task efficiency.

✉ Nina Passlack
nina.passlack@uni-bamberg.de

[1] Information Systems and Social Networks, University of Bamberg, An Der Weberei 5, 96047 Bamberg, Germany

While efficient outcomes focus on maximizing utility related to time, finance, and other resources (Reinhardt, 1992), responsible human-AI interaction requires consideration of the potential consequences of human-AI interaction that can produce unintended side effects (Kegel & Ghanem, 2024) with respect to employee well-being, fairness, other social implications, and so on. While these responsibility dimensions may not directly affect efficiency in the short term, they may in the long term (Benlemlih & Bitar, 2018). Recognizing the need for organizations to remain competitive and financially sustainable, we acknowledge the crucial role of efficiency in enabling responsible human-AI interaction. Yet, we argue that focusing mainly on AI literacy that facilitates process efficiency in human-AI interaction is a one-sided approach. We suggest instead that knowledge workers must balance multiple factors to ensure responsible outcomes in human-AI interaction. Since inequalities may exist that divide certain groups of people from others, as outlined by Zamani and Vannini, we argue that a lens of digital responsibility is essential when conceptualizing AI literacy, in order to prevent such unintended consequences.

This requires a digital responsibility perspective to mitigate the lack of abilities required for responsible human-AI interaction. Consider, for instance, the introduction of AI in organizations with a focus on training knowledge workers in skills to make quicker and more precise decisions, which could make work practices more effective in the short term (Mayer et al., 2020). Not preparing those same knowledge workers profoundly for AI's impact on their work practices might, for instance, lead them to see AI as a threat to their identity in the long term (Mirbabaie et al., 2022; Parker & Grote, 2022). People may have difficulties understanding the processes behind AI and have issues defining their roles in the context of human-AI interaction (Benbya et al., 2021). This issue becomes particularly concerning when individuals are unaware that using AI can lead to moral violations. For example, medical AI used for diagnostics in healthcare may be trained on datasets that are not representative of all populations, potentially resulting in higher misdiagnosis rates for certain ethnic groups (Lebovitz et al., 2022; Yokoi et al., 2021). Thus, responsibility gaps can occur when it comes to unintended outcomes of human-AI interaction (Smith & Vickers, 2021), requiring a more conscientious approach that pays greater attention to what fosters *responsible* human-AI interaction. We aim, therefore, to answer the following research question:

What Shapes AI Literacy for Responsible Interactions of Knowledge Workers with AI?

After synthesizing existing conceptualizations of AI literacy and outlining the different aspects, building blocks, related literacies, and analysis levels of AI literacy in our theoretical background, we conducted qualitative interviews ($n=28$) with five different groups of knowledge workers to account for different professional perspectives on human-AI interaction and thus answer the research question. Our key findings highlight tensions that challenge the conceptualization of AI literacy through the lens of digital responsibility and the examination of factors that influence responsible human-AI collaboration. Our analysis does not claim to provide an exhaustive account of all components relevant to AI literacy; rather, its primary aim is to offer a perspective on rethinking the concept of AI literacy by highlighting which constructs become relevant when the objective is not only effective but also responsible human-AI interaction. We emphasize moving beyond a narrow focus on efficiency, highlighting the need for AI literacy to equip knowledge workers not only with technical skills but also with the capabilities to engage with AI systems in an ethically sound, accountable, and context-sensitive manner and thereby consider possible influencing factors that shape responsible interaction with AI.

While different perspectives exist, our interviews emphasize the importance of users' personal dispositions, human-centered aspects, ethical literacy, and the factors influencing AI literacy development across micro-, meso-, and macro-levels, all of which are crucial to consider for fostering responsible human-AI interaction. Finally, we emphasize the critical importance of achieving what we call the "role-ability fit" – the alignment between the responsibilities assigned to individuals in specific roles and their capacity to act responsibly and be held accountable for those duties. This insight leads us to underscore the growing relevance of "multi-literacy" – the ability of knowledge workers to navigate and understand diverse domains, enabling them to engage responsibly with AI technologies. Furthermore, given that AI technologies involve multiple stakeholders across different phases of development and application, establishing shared responsibility is indispensable. We suggest, only through this collective responsibility can we ensure that human-AI interactions are ethically sound and socially beneficial.

We see our work contributing to the field of Information Systems (IS) in two key ways. *First*, we contribute to IS research by enhancing previous conceptualizations of AI literacy with an empirical analysis of components that become increasingly relevant to dealing with AI technologies *responsibly*. Thereby, we rethink the concept of AI literacy through a lens of digital responsibility and investigate knowledge workers' perceptions regarding the evolving importance of abilities in the context of AI-driven transformation, with particular focus on responsible human-AI interaction. Our research thereby outlines how perceptions may vary across knowledge workers and how understanding the concept of AI literacy as a modular concept may allow us to account for these diverse roles and perspectives. This approach also helps to identify which components of AI literacy may become particularly critical in ensuring responsible human-AI interaction. *Second*, our study outlines potential tensions in responsibility and influencing factors that impact the development of AI literacy among the workforce, which can be a challenge for the strategic management of AI in organizations. We outline problems that may hinder responsible human-AI interactions within organizational settings and propose possible strategies to support organizations in fostering responsible human-AI interactions.

The next section provides the theoretical background for our research. We then describe the methods used in our qualitative study. The fourth section presents our results, followed by a discussion of the problems identified. The paper ends with a conclusion section.

2 Theoretical Background

This section identifies prior conceptualizations of AI literacy (Section 2.1) and establishes theoretical foundations for understanding the importance of responsibility in human-AI interactions (Section 2.2). The procedure for reviewing the existing literature is detailed in Appendix 1.

2.1 AI Literacy, its Components, Related Literacies, and Possible Analysis Levels

Figure 1 presents an overview of potential AI literacy components relevant to people interacting with AI. Through our interviews, we aim to identify which of these components are essential for the responsible design, deployment, and use of AI technologies, as well as the management of human-AI interactions, to provide a holistic view of components relevant to knowledge workers interacting with AI. As Fig. 1 demonstrates, our findings from the literature consist of different *aspects*, *building blocks*, *technology-related literacies*, and different *analysis levels* that may influence the concept of AI-literacy and its development. Depending on the use case and context of human-AI interaction, specific combinations of these elements may become critical. Thus, we understand AI literacy as a toolbox, with each use case requiring a unique combination of specific aspects and building blocks, and being encouraged by other related literacies.

Literacy Aspects The academic discourse on literacy in the context of technology has proposed several classifications to distinguish different aspects of literacy. We categorized the factors into technical aspects – those directly related to understanding the AI – and human-centered aspects, which are also relevant in human–human interaction settings. For instance, McLean (2013) suggests that there are three

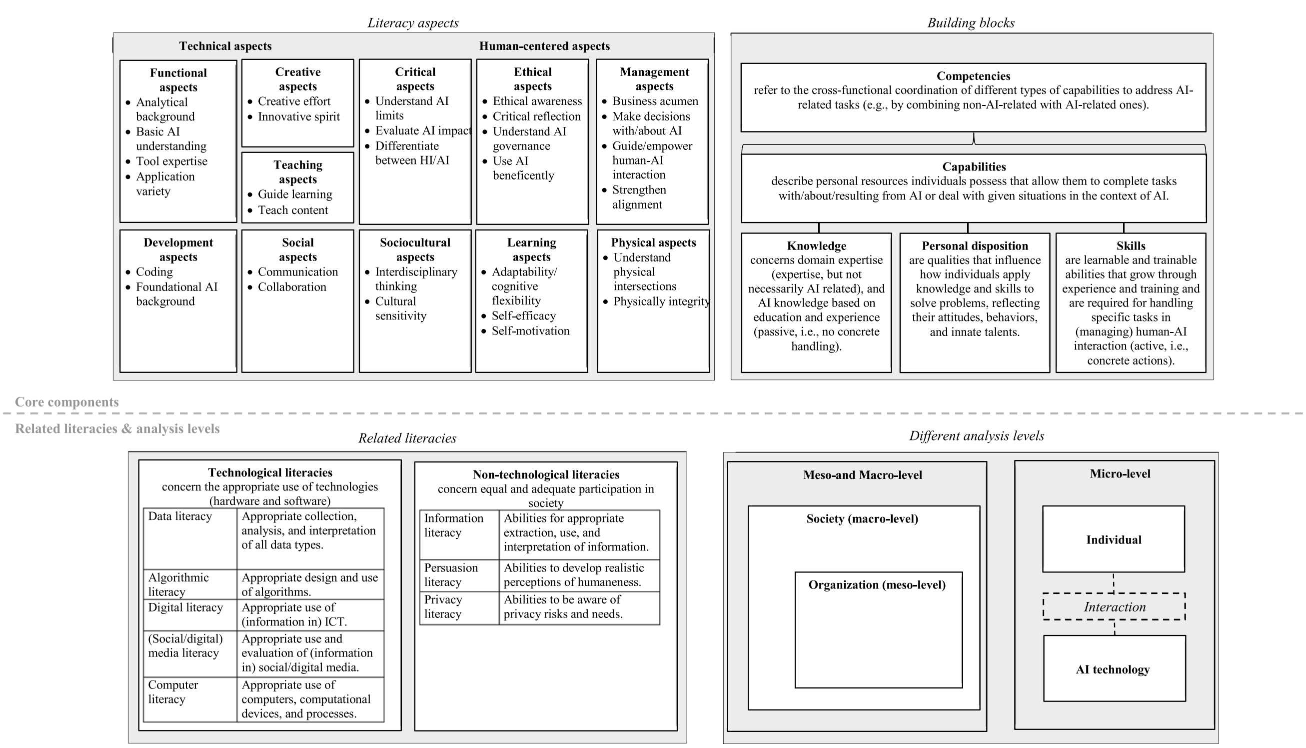

Fig. 1 Components of AI literacy

dominant literacy discourses that shape approaches to literacy in a technological context, which are differentiated into functional, critical, and socio-cultural. Adapting these notions, we propose that the *functional aspects* encompass the technical and analytical abilities required to manage data and use technologies effectively, such as basic AI understanding, which prior research has confirmed as key components of AI literacy (e.g., Carolus et al., 2023; Laupichler et al., 2022, 2023; Long & Magerko, 2020; Verma et al., 2022). The *critical aspects*, in turn, concern awareness of AI's impact on individuals, organizations, and society, as investigated, for instance, by Hermann (2022). Finally, the *socio-cultural aspects* focus on understanding the influence of cultural contexts on AI's outcomes, which is important to consider (Sanusi et al., 2022a, b).

Our review further highlights, however, that with AI advances and the partially uncertain consequences of human-AI interaction, additional aspects are becoming increasingly important and warrant further exploration. By *ethical aspects,* we refer, for instance, to the ability to recognize and navigate ethical conflicts and concerns, which has also been found to be part of AI literacy (Ng et al., 2021); yet, there is empirical research missing on how to foster those ethical aspects. By *learning aspects,* we refer to fostering one's interest in learning, being cognitively flexible, and having the ability to adapt dynamically (Martini & Sénéchal, 2012). While further research is required on how to "promote responsible … evolution of AI tools" (Dwivedi et al., 2023, p. 6), our focus is on understanding how learning aspects can provide support in this regard. S*ocial aspects* encompass communication and collaboration through and with AI, being identified for effective use of AI (e.g., Anton et al., 2020; Long et al., 2022), becoming particularly critical in case of unintended and unpleasant outcomes. As we suggest, *creative aspects* involve the identification of solutions to problems in the sense of problem solving (Ali et al., 2021; Anton et al., 2020; Su & Yang, 2023); more research is needed to explore how creativity can be applied when addressing responsibility issues. Finally, *physical aspects* are essential, as it is crucial to "understand that some AI systems can physically act on the world" (Long & Magerko, 2020, p. 6), such as in "robot-assisted surgeries" (Jaiswal et al., 2022, p. 1190). Given the broad spectrum of AI literacy components relevant to human-AI interaction, our empirical investigation aims to identify which aspects are most critical to ensuring responsible outcomes and to explore the factors that influence their development.

The literature also highlights the possibility of further literacy aspects that may be particularly relevant for specific technologies and groups of knowledge workers. For instance, we identified what we term *managerial aspects*, which encompass the ability of leaders and managers to recognize business opportunities and challenges arising from AI transformation, to make informed decisions grounded in business acumen, and to build trust while guiding their teams, all of which are essential for working with AI effectively (Alsheiabni et al., 2019; Anton et al., 2020). However, a gap remains in understanding how managerial dimensions are influenced by specific factors that hinder responsible human-AI interaction. *Developmental aspects* concern the ability to program and develop AI technologies, including preliminary ideas regarding how to do so responsibly, such as being attuned to biases in the data (Ng et al., 2021).

To summarize, AI literacy aspects are one component of AI literacy that requires deeper exploration to determine how these aspects can contribute to responsible human-AI interaction. Thus, our investigation seeks to explore how certain knowledge workers may possess specific literacy aspects that could foster responsible human-AI interaction.

Building Blocks Through the review, we found that AI literacy includes different building blocks, namely skills, knowledge, personal dispositions, capabilities, and competencies. Although these building blocks are often used synonymously, they represent distinct concepts that collectively form literacy (Bawden, 2008).

Skills are learnable and often "task-specific" as they grow with experience (Yamaguchi, 2018), and hence can be developed through education and experience (Gabric & McFadden, 2001). *Knowledge*, by contrast, refers to the awareness and understanding of facts and information being analyzed and is based on an individual's education and experience (Dalkir, 2013, p. 8). This means that "knowledge is information possessed in the mind of individuals" (Alavi & Leidner, 2001, p. 109). Knowledge can be what is often called domain knowledge, which refers to profound knowledge and expertise in a specific domain or context (Bradley et al., 2006), or meta-knowledge, such as knowing "who knows what" in the sense of "knowledge about knowledge" (Evans & Foster, 2011, p. 721). Some researchers (e.g., Hemment et al., 2023; Sanusi et al., 2022a, b; Su & Zhong, 2022) further underscore in the literature the importance of what we call *personal dispositions*, which "are affective or dispositional qualities, encompassing attitudinal, behavioral, and socio-emotional qualities of how disposed people are to apply knowledge and skills to solve problems or address issues of personal, social, or workplace-related interest" (Frezza et al., 2018, p. 155). Thus, personal dispositions also define "how much the learner makes the content and skills his or her own" (Frezza et al., 2018, p. 154). They may include interest or aptitude (Ferguson, 1960), but also implicit motivation, which constitutes a person's natural endowments

– innate capabilities that exist independently of the external environment (Ferguson et al., 2008).

Capabilities are linked to the deployment of knowledge and skills, as well as personal dispositions, to complete tasks or deal with given situations (Wahl & Prause, 2013); they arise from external forces and grow with experience and/or education. It should be noted that capabilities also include talent and aptitude as "a joint function of ability and interest" (Ferguson, 1960, p. 131). *Competencies*, by contrast, are the "cross-functional integration and coordination of capabilities" to address tasks (Wahl & Prause, 2013, p. 67); they build on capabilities by combining knowledge, skills, and attitudes.

The diverse array of building blocks that comprise AI literacy – ranging from skills, knowledge, and capabilities to competencies and personal dispositions – underscores the complexity of achieving responsible human-AI interaction. While existing theoretical frameworks provide a foundational understanding of these components, there remains a critical need for empirical research to determine which of these building blocks become particularly relevant in order to guarantee responsible human-AI interaction. Understanding which building blocks are most pertinent allows us to develop more targeted strategies for enhancing AI literacy for responsible interaction.

Related Literacies Our literature review reveals several interdependencies between AI literacy aspects and aspects of other forms of literacy, showing the importance of recognizing the range of literacies that may be related and therefore also relevant to AI literacy.

Prior literature further highlights connections between AI literacy and other literacies in a technology context. For instance, *data literacy* – the ability to collect, analyze, structure, and interpret data (Qin & D'ignazio, 2010) – can be considered a prerequisite for AI literacy (Anton et al., 2020; Jaiswal et al., 2022). *Algorithmic literacy* – understanding and appropriately utilizing algorithms (Ridley & Pawlick-Potts, 2021) – is further related to AI literacy in that it intersects with data literacy and digital literacy (Anton et al., 2020; Jaiswal et al., 2022). *Digital literacy* is the ability to interact effectively with digital tools such as information and communication technologies (ICTs) (Gilster, 1997; Reddy & Sharma, 2020). It, thus, includes *information technology (IT) literacy*, which also encompasses interacting with information embedded in various technologies (Reddy & Sharma, 2020). While not all researchers explicitly use the term "digital literacy," many suggest that it plays a significant role in AI literacy: some acknowledge overlapping areas (e.g., Anton et al., 2020; Wang et al., 2022), while others argue that digital literacy is a prerequisite for AI literacy (e.g., Cetindamar et al., 2022; Jaiswal et al., 2022; Long & Magerko, 2020; Markauskaite et al., 2022).

Information literacy and *media literacy* (including social and digital media literacy) are also connected to AI literacy (Hermann, 2022): (social or digital) *media literacy* is the ability to engage critically with information presented through various online media channels (Manca et al., 2021), while *information literacy* is the ability to identify, understand, and work with necessary information (Boichak et al., 2019; Rosenfeld, 2016). *Computer literacy* is the ability to demonstrate basic computer operation and application use skills (DiSessa, 2018, p. 4), and thus is also related to AI literacy. Most recent literature also introduces *privacy literacy* "as the ability to manage, protect privacy, and identify privacy risks" (Carolus et al., 2023, p. 5), while one paper introduces *persuasion literacy*, that can be defined as "understand[ing] how human-like features" can impact humans' perceptions of AI (Carolus et al., 2023, p. 5) as related literacy.

This shows that literacies are inherently interconnected, as being literate in any given situation often requires the integration of multiple aspects of different literacies (Lankshear & Lawler, 1987). Multi-literacy refers to the simultaneous application of various literacies within a single context (Luke, 1997). It can be understood as "emphasizing different kinds of …literacies to help [individuals] to become skilled at moving among them in strategic ways" (Selber & Selber, 2004, p. 24). In the context of responsible human-AI interaction, it is crucial to recognize the range of literacies that may also be relevant. Thus, AI literacy may be viewed as a multi-literate concept, with different use cases determining the particular literacies required for responsible human-AI interaction. Our empirical investigation explores distinct intersections of literacies to make individuals literate for responsible human-AI interaction.

Different Analysis Levels Human-AI interactions in organizations can be understood as socio-technical systems that outline interdependencies between humans, technologies, and organizational elements (Leonardi, 2012). As a consequence, human-AI interactions shape patterns of action in organizations (Cecez-Kecmanovic et al., 2014), and, as a consequence, AI literacy can also be influenced by factors at various levels of analysis. Analysis at a *micro-level* can provide insights into the aspects that influence individuals to interact effectively with AI technologies, recognizing that AI is transforming how individuals communicate and work (Long & Magerko, 2020). Thus, at the micro-level, factors from both the individuals and the technologies may influence requirements for literacy for responsible human-AI interaction. Analysis at a *meso-level* investigates AI literacy that enables organizations to deploy AI (such as Mikalef and Gupta (2021) investigated). It comprises "the abilit[ies] of a firm to select, orchestrate, and leverage its AI-specific resources" (Mikalef & Gupta, 2021, p. 2). At a *macro-level,* AI literacy can be analyzed from a global perspective (Kathala & Palakurthi, 2024). The literature discusses, for instance, which skills are needed to recognize AI-generated deepfakes and misinformation that have an impact on society (Ali et al., 2021). However, further insights are needed into how factors across different levels of analysis influence knowledge workers' AI literacy in the context of fostering responsible human-AI interaction.

To conclude, Fig. 1 illustrates that AI literacy is a multi-faceted concept that can be analyzed on different levels, is composed of multiple interrelated components, and is closely related to other forms of literacies. While in some situations, specific literacy aspects become relevant to human-AI interactions, which is linked to the term upskilling (Morandini et al., 2023), in certain situations, other abilities may become less relevant or unlearned through increased reliance on AI, which can be linked to deskilling (e.g., Rafner et al., 2022). We aim to shed light on both upskilling and deskilling by discussing how this may foster or pose challenges to responsible human-AI interaction. Moreover, our interviews explore how to rethink the concept of AI literacy with respect to relevant components of AI literacy. In doing so, we understand AI literacy as a flexible toolbox, with different tasks and professional roles demanding a distinct mix of aspects and building blocks. It is further shaped by related literacies and influencing factors across different levels of analysis.

2.2 Heading from Efficient Toward Responsible Human-AI Interaction

Recent literature underscores the need for a shift from prioritizing efficiency to emphasizing responsibility in human-AI interaction, challenging traditional concepts of AI literacy. For instance, Oeldorf-Hirsch and Neubaum (2023) argue that while some people may possess high self-efficacy and cognitive skills for engaging effectively with social media algorithms, their literacy often falls short when considering the broader consequences. The authors highlight that specific groups of people, such as the LGBTQ+communities, have to "face extra challenges in terms of their literacy to make algorithms in constantly changing social systems work for them" (Oeldorf-Hirsch & Neubaum, 2023, p. 28). This observation suggests that AI literacy must extend beyond the efficiency of using algorithms to include an awareness of the social and ethical implications of their use to avoid discrimination and exclusion of certain groups of people (Celik, 2023). Oeldorf-Hirsch and Neubaum (2023) advocate for enhancing literacy by making users aware of potential biases, as well as for improving developer literacy to ensure the responsible design of social media algorithms and thereby avoid exacerbation of social inequalities. This shift reflects a broader move from focusing solely on efficiency toward integrating responsibility within the concept of literacy to balance efficiency and responsibility.

Similarly, Bankins et al. (2024) argue that current AI research is divided between studies that focus on the skills and knowledge necessary to maximize technological efficiency and those that examine the impact of AI on human workers, particularly regarding their self-confidence and emotional well-being. The prevailing emphasis on performance, characterized by increased efficiency and optimized resource use, often overlooks the responsible deployment of AI technologies (Passlack et al., 2024). For human-AI interactions to be truly responsible, it is essential to consider not only the immediate technical outcomes but also the broader, often unintended, consequences on human labor and societal well-being (Bankins et al., 2024).

In light of these discussions, the concept of **digital responsibility** gains increasing significance when considering the components that constitute AI literacy for responsible human-AI interaction. Digital responsibility encompasses the responsible design, implementation, and adoption of digital technologies, particularly during digital transformation efforts. More concretely, the principle of digital responsibility can be defined "as a fundamental and value-based normative requirement that motivates actors to attain responsible digital transformation" (Trier et al., 2023, p. 464). There is a growing need for empirical insights across various use cases of knowledge workers' engagement with AI to understand what shapes responsible interaction with AI and also how to responsibly address the potential harms of AI technologies while effectively harnessing their benefits (Pappas et al., 2023).

Several digital responsibility-related frameworks exist in the academic discourse. For instance, discourse around responsible AI emphasizes the design and implementation of AI technologies in real-world settings, guided by ethical principles such as fairness, explainability, and accountability (e.g., Arrieta et al., 2020; Trocin et al., 2023). The concept of corporate digital responsibility (CDR) advocates for human-centric approaches to manage human-AI interaction responsibly within organizations, emphasizing common values and standards that guide how digital technologies and data are developed and used (e.g., Kunz & Wirtz, 2024; Pappas et al., 2023; Trier et al., 2023). Such frameworks, though, are often related to single perspectives of responsibility and are often very abstract. Therefore, our research aims to explore on a meta-level how digital responsibility is and can be embedded within AI literacy investigations.

Through empirical interviews with different knowledge workers, we provide insights into the specific abilities required to interact with AI technologies responsibly and the arising tensions.

In this work, we further conceptualize digital responsibility in human-AI interaction as encompassing two key dimensions: the state of *being responsible* and *acting responsibly*. We suggest that acting responsibly involves the proactive consideration of potential unintended consequences during the interaction with AI, grounded in people's ability to reflect on their behavior and morally evaluate specific outcomes (Eshleman, 2014). Someone *acting responsibly* is expected to adhere to socially accepted and approved behavioral standards, aligning with the expectations placed on "accountable" actors as outlined by Lerner and Tetlock (1999). In contrast, *being responsible* pertains to the attribution of responsibility assigned per duty, and is often linked to a person's role (Hamilton & Hagiwara, 1992). "To be responsible for an outcome and to act responsibly may still be linked in the sense that a responsible person is prepared to accept the consequences of his or her actions, and thus acts in accordance with anticipated judgments of responsibility, rather than just be blamed or praised after the fact." (Nordbye & Teigen, 2014, p. 102). People who act irresponsibly could still be responsible. Indeed, it can be argued that they should feel and be held responsible, particularly for irresponsible behavior (Nordbye & Teigen, 2014).

Acting responsibly when interacting with AI, thus, necessitates certain abilities linked to the aspects introduced in Section 2.1; without these, people lack control over their actions and, consequently, it can be perceived as inappropriate to hold them accountable (Horneber & Laumer, 2023; Martin, 2019). For instance, AI systems used in recruitment processes, such as online assessments, may inadvertently discriminate against individuals with specific conditions, such as dyslexia. In such cases, human intervention is essential to ensure the fairness of the process (Malik et al., 2021). While AI can increase efficiency by reducing the need for human involvement in the selection process, exclusive reliance on AI for decision-making requires a clearer attribution of responsibility within the human-AI interaction. To ensure responsible practices within this context, we suggest that recruiters must develop AI literacy that enables them to recognize and address potential conflicts.

The state of **being responsible** is tied to the specific duties associated with individual roles or the accountabilities of knowledge workers as defined at the organizational level, which involves taking responsibility for achieving certain outcomes. As an example, managers can be made responsible for the effective implementation of AI within organizations (Alsheiabni et al., 2019). Individuals in such roles, however, may lack the necessary abilities associated with AI maturity, which constitutes a prerequisite for fully assuming the responsibility inherent in their positions (Alsheiabni et al., 2019). Thus, enhancing AI literacy is crucial as it can facilitate the behavioral changes necessary to fulfill these roles. Otherwise, responsibility gaps may emerge, particularly in relation to the unintended outcomes of human-AI interaction (Matthias, 2004; Smith & Vickers, 2021). Thus, we argue that responsible human-AI interaction requires an understanding of the complex nature of responsibilities that shape what it means for individuals to "be responsible" in these interactions. Given that various knowledge workers are involved in human-AI interaction, we discuss this complexity in our work.

Consequently, we suggest both dimensions – acting responsibly and being responsible – to be critical. For instance, while people may be held legally or morally responsible for certain AI operations, such as when pilots operate autonomous cockpits, the erosion of their decision-making authority and manual skills can create a disconnect between their responsibilities and their control over systems (Holford, 2022). Aligning knowledge workers' role-based responsibilities with their ability to act responsibly requires the *role-ability fit*, which we define as the alignment between individuals' prescribed responsibilities based on their roles (being responsible) and their actual AI literacy abilities required to fulfill those responsibilities (acting responsibly). There is a need to explore how the abilities of individuals and AI can contribute to fostering responsible human-AI interaction (Trocin et al., 2023).

To summarize, using the concept of digital responsibility in our work helps us by providing a lens to better understand the abilities that drive knowledge workers to interact with AI technologies responsibly and in a manner that proactively considers potential harms and maximizes benefits. It involves acting responsibly – by ensuring that knowledge workers have the ability to reflect on the unintended consequences of AI technology use – and being responsible, which entails taking responsibility based on one's role and duties. We investigate this based on our empirical insights from interviews with different groups of knowledge workers.

3 Research Design: Qualitative Interviews

We conducted semi-structured interviews with different groups of knowledge workers to deepen our understanding of what shapes *responsible* human-AI interaction that considers but goes beyond efficiency. Thereby, we aimed to extend the "evolving set of ideas that emerge …within and among scholarly communities" through "learning with and from practitioners" (Burton-Jones et al., 2021, p. 306). We deemed interviews to be a suitable method as they can provide insights into individuals' thoughts, motivations, and experiences that cannot be obtained through quantitative data (Sarker et al., 2013). In doing so, we aimed to make sense of AI literacy for responsible human-AI interaction as an object. While prior research offers conceptualizations of AI literacy, our study aims to explore how people understand and perceive the promotion of responsible human-AI interaction. Interviews have proven to be a good approach for achieving a better understanding of social phenomena (Myers & Newman, 2007). Given that "responsible human-AI interaction" is an intangible construct that is difficult to quantify and measure, the interviews enabled us to examine the concept of AI literacy, in which predefined variables remain unclear and challenging to articulate. Furthermore, employing interviews acknowledges the complexity of combining the concept of responsibility with AI literacy, which is shaped by individual experiences rather than being reducible to numerical data. By conducting interviews, we were able to generate propositions that can now be tested using quantitative methods. The interviews helped us reflect upon different use cases by interviewing diverse professional groups (see 3.1), searching for AI literacy components required for interacting with AI in a responsible way, and investigating influencing factors such as potential challenges and tensions in establishing them.

3.1 Sampling

To ensure a cross-section of knowledge workers in different use cases of human-AI interaction, we deliberately selected participants from five stakeholder groups chosen to capture a broad range of perspectives on AI literacy, ensuring that insights reflect varied contexts and AI literacy abilities required across different professions. The stakeholder groups and their selection criteria are: HR professionals (H) responsible for hiring and training employees to develop AI-related abilities among the workforce, thus providing an operational perspective; managers (M) responsible for AI deployment in organizations, thus providing a strategic perspective; AI designers and data scientists (D) who are experts in designing, developing, training, and fine-tuning the underlying AI models and their applications, thus providing a developmental perspective; researchers and educators (R) who teach and train on relevant AI literacy abilities, thus providing an educational perspective; and sales and product managers of AI technology providers to businesses (S), who add a consumer-producer perspective. All our interviewees (see Appendix 2 for details) have a minimum of three years' experience in their fields and direct experience in AI-related tasks. Table 1 is an overview of the different stakeholder groups.

We recruited participants through targeted outreach via LinkedIn and email, selecting individuals based on their public professional profiles and their expertise in AI-related activities. Potential participants were provided with information about the research project, including its aims, expected contributions, and the interview structure. Data collection took place between March 2023 and September 2024. All interviews were conducted in German by telephone ($n=2$) or video call using Zoom or Teams ($n=26$), and included one interviewer and one person taking notes. The interviews, which lasted an average of 42 min, were recorded and transcribed, and subsequently translated into English. In total, we conducted 28 interviews.

3.2 Semi-Structured Interviews

We employed a semi-structured interview guide (Myers & Newman, 2007) to ensure that "standard procedures are used from one interview to another" (Crewswell, 2014, p. 194). The interview guide (see Appendix 3) was pre-tested on three pilot interviewees to ensure the clarity of the questions. The semi-structured interview guide has four main sections. In the first section, interviewees are asked about their background and working context, such as the work culture and the role AI plays for them at work. In the second part, interviewees are asked to describe different scenarios in which AI-based technologies are developed, sold, deployed, managed, educated about, or used in their business contexts. The third section focuses on what constitutes

Table 1 Interviewed groups of knowledge workers

Reference	Selection criteria	Perspective	N
H	HR professionals responsible for hiring and/or training employees (to become) familiar with the AI abilities the organization requires and who advocate for workforce AI literacy at the operational level	Operational perspective	5
M	Managers with decision-making responsibility for the implementation and use of AI in the organization and who may, therefore, provide a strategic perspective on AI literacy	Strategic perspective	6
D	Developers, data scientists, and AI specialists who use their AI knowledge to design/develop and/or use AI-based technologies, to train and fine-tune the underlying AI models, or advise on AI implementation projects	Developmental perspective	6
R	Educators and researchers (e.g., schoolteachers, professors) who teach AI literacy and train individuals to become familiar with AI capabilities in their daily lives	Educational perspective	5
S	Product and sales managers working for AI providers who distribute AI-based technologies to business clients; they were included to ensure that we would have a consumer-producer perspective from the business-to-business (B2B) sector as part of our analysis	Consumer-producer perspective	6

AI literacy for responsible human-AI interaction, based on the examples provided by the interviewees. By analyzing the examples and different use cases involving different AI technologies, we analyzed which components of AI literacy may be seen as increasingly relevant when transitioning from a sole focus on efficient human-AI interaction to a broader emphasis on responsible human-AI interaction. In the fourth section, we asked interviewees what factors on different levels – such as society (macro-level), their organization (meso-level), or themselves as individuals (micro-level) – influence and foster the development of AI literacy for responsibility in human-AI interaction.

3.3 Data Analysis

We followed a mainly deductive and partially inductive coding process based on Mayring (2014) for qualitative analysis of the 28 interviews. First, we aimed to identify relevant components of AI literacy that knowledge workers perceived as being relevant for responsible human-AI interaction. Following deductive coding, we used the components that we derived from the literature in the first stage (as visualized in Fig. 1) involving literacy aspects (further split into human-centred aspects and technological aspects), building blocks, etc., to establish categories with definitions, anchored examples, and coding rules (Mayring, 2014, p. 95). We then assigned text passages from the interviews to those categories and formed subsequent categories inductively during the coding process, when we explored novel phenomena that we could not aggregate within our existing categories (Mayring, 2014, p. 80). The different codes linked to the literacy aspects were then assigned to the related literacies (e.g., digital literacy, data literacy, etc.).

We also coded what hinders the development of relevant abilities and how they can be fostered, where we inductively created categories. We thereby adhered to the knowledge workers' framing of influencing factors, ensuring that our analysis remained aligned with their descriptions. We then mapped the identified influencing factors to the different analysis levels that we derived deductively in the theoretical background (see Section 2.1).

Moreover, we coded the different use cases that were addressed in the interviews, synthesized them, and categorized them into six distinct groups ("decision-making," "creation and information," "prediction," "optimization," "physical," and "communicative and supportive" tasks) to reveal any differences in skill requirements between use cases, as presented in Appendix 5. Measures to foster AI literacy were also coded inductively and linked to the specific use cases in which they were mentioned. To ensure reliability, the coding scheme was developed collaboratively by two coders. Appendix 4 provides a snapshot of the coding.

Building on this, we analyzed the coded data to answer our research question regarding what shapes AI literacy for responsible interactions of knowledge workers with AI. When analyzing the prevalence of themes in participant responses, we realized that certain components were named more often, which suggested to us a need to rethink current AI literacy frameworks. We also identified differing perspectives among knowledge workers, for istance, regarding which abilities can be developed through training and which should already be part of a person's disposition (such as moral values). Furthermore, we identified which aspects are considered essential for responsible human–AI interaction and which factors influence the development of these abilities – insights discussed further in Section 4.

3.4 Data Quality

To demonstrate the rigor and quality of our interview-based research, we provide a transparent and explicit discussion of validity. In particular, we sought to ensure descriptive and design validity by systematically conducting and carefully documenting the interviews using a structured interview guide (Sarker et al., 2018). To prevent the loss of valuable information, all interviews were transcribed in full, ensuring that the researcher's protocol was not the sole basis for analysis. In addition, each interview was conducted with two researchers present – one leading the interview and the other taking notes. This dual-researcher approach added an extra layer of interpretation accuracy beyond the transcripts alone, further strengthening validity (Myers & Newman, 2007). To enhance interpretive and analytical validity, we engaged in simultaneous transcript coding, fostering a shared understanding and consistency in interpretation. We also aimed to secure theoretical and inferential validity by systematically documenting the coding process, including defintions for each category supported by illustrative interviewee quotes, and developing a detailed coding scheme collaboratively. This scheme was continuously refined through coder discussion and repeated training, ensuring consensus and readability in the interpretation of the data (Garrison et al., 2006).

4 Results: What Shapes AI Literacy for Responsible Interactions of Knowledge Workers With AI?

The following section presents our key findings based on the analysis of the interviews. While we do not claim to provide an exhaustive account of all components relevant to AI literacy, our aim is to contribute a perspective on how the concept of AI literacy might be rethought. We seek to move beyond a narrow focus on efficiency and instead emphasize the need for AI literacy to support *responsible* interaction. This shift in perspective underscores the importance of equipping knowledge workers not only with the technical skills to work with AI but also with the capabilities to engage with AI systems in an ethically sound, accountable, and context-sensitive manner. We identified core components that knowledge workers perceive as enabling responsible interaction with AI, alongside influencing factors across different analysis levels that may challenge skilling processes for this enablement. While Fig. 1 presents a synthesis of existing conceptualizations of AI literacy, we focus in this results section on how the concept of AI literacy must be rethought for *responsible* human-AI interaction, resulting in Fig. 2. From the findings we suggest that while there are tensions and different views, guaranteeing *responsible* human-AI interaction requires awareness of the importance of knowledge workers' personal dispositions (Section 4.1), the need for human-centered aspects of AI literacy (Section 4.2), the need of ethical literacy (Sect. 4.3), and factors that influence AI literacy development across different levels (Section 4.4). In the following sections, we elaborate on these four key findings by summarizing the findings from our interviews.

4.1 Personal Dispositions Gain Relevance for Responsible Human-AI Interaction

Concerning the building blocks relevant to AI literacy, our data analysis outlined the importance of personal dispositions to foster individuals "feeling responsible" and thus responsibly interacting with AI technologies. Our interviews highlighted that since AI is continually evolving, AI literacy is not static but requires the motivation and mindset for continual learning and moral values to guarantee responsible interaction with AI.

Responsible AI usage was shown to go beyond having certain skills and knowledge, with a majority of codes related to what we defined as personal disposition (58.16%) compared to knowledge (25.52%), skills (11.22%), capabilities (4.08%), and competencies (1.02%). Concerning personal dispositions, patience was mentioned as important (e.g., D1, S2) as "there are a lot of stumbling blocks" (S2, p. 12) when first implementing AI, as well as forward-thinking and an "open mindset for challenges" were reported as critical (e.g., S2, M2). This means an awareness that each "[AI] project has its own difficulties, so you have to expect and embrace them" (S2, p. 12). Personal dispositions also include having a deep-seated drive for self-learning and being open to creating one's own experiences with AI (e.g., M4, D5, S5) to be prepared for rapid AI progress that leads to technical skills becoming outdated (e.g., S2, S6). At the same time, responsible interaction with AI was reported to require being able to scrutinize opposing interests with a "healthy skepticism" (D5, p.8). While a healthy skepticism does not necessarily increase performance, it was reported to be a precondition for the responsible use of AI. As one developer described: "You're not relying on it blindly, but you check it again with your own knowledge and conscience" (D1, p. 3). While this may, to some extent, contradict efficiency, it was reported as relevant to responsible

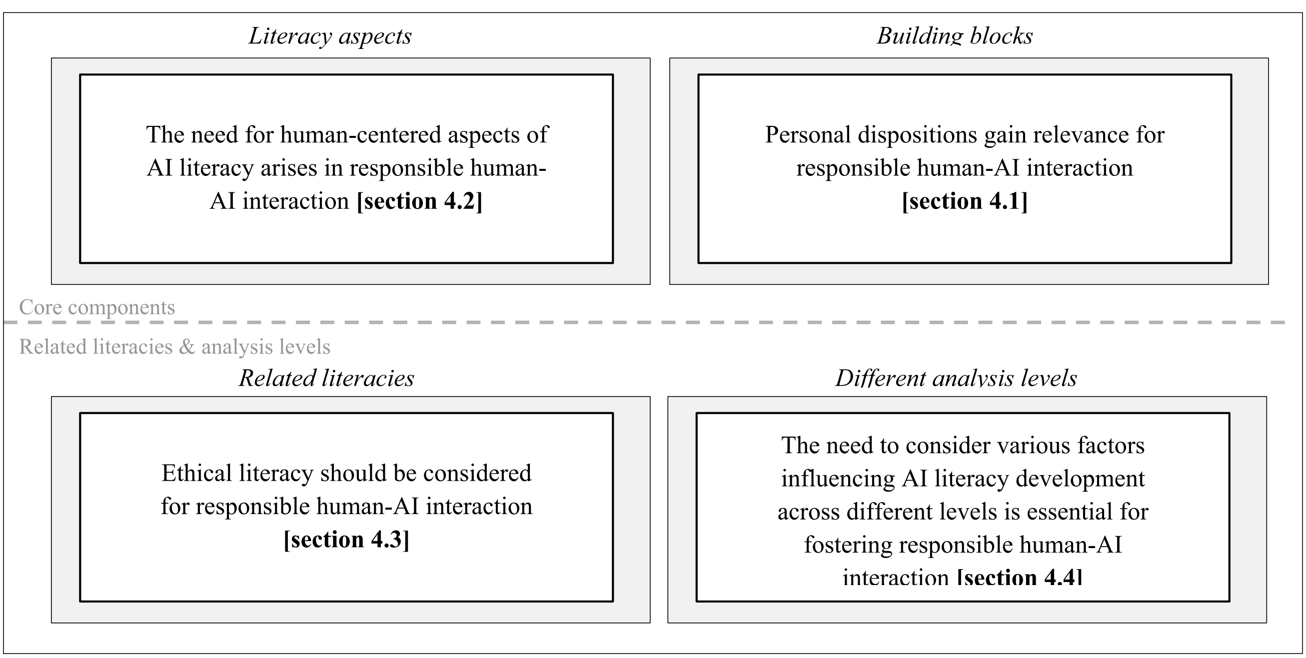

Fig. 2 Moving from efficient toward responsible AI literacy

interaction. This illustrates that personal dispositions may be highly relevant building blocks of AI literacy when it comes to responsible interaction with AI.

Yet, the analysis shows different perspectives regarding fostering personal dispositions. Some interviewees suggested that certain factors need to be anchored in a person's disposition as a prerequisite for being able to interact with AI responsibly. Others, though, argued that personal dispositions are influenced by and develop through different training. The following sections elaborate on these two perspectives.

Personal Dispositions Are a Prerequisite for Responsible Interaction With AI One perspective suggests a shift away from a competence profile involving several skills and knowledge to a profile of individuals' moral values and dispositions that make them literate to deal with AI responsibly. Some interviewees argued that personal dispositions cannot be taught or acquired through learning, and thus, individuals require a certain foundation of personal dispositions (e.g., S3, S2). As one salesperson framed it: "I believe that the skills are indeed more about the soft skills … particularly the mindset. This is because it is a skill that cannot be developed or learned but rather is intrinsically present. Only in a second step does familiarity or interaction with technology, or specifically AI, become relevant." (S2, p.9).

Moral intuition, for instance, was identified as an essential inherent personal resource to evaluate AI's output, which some expect to be anchored in a person's virtue ethics. Some suggested that since moral values differ (e.g., R1, S3), morality is lived differently, depending on the environment and shaped by experience and society. For instance, "what are the fairest criteria?" (S5, p. 13) asked one participant by stating that reflections of fairness depend on individual moral character and virtues. However, these virtues can be viewed as less learned compared to technical skills (e.g., M2). Managers who suggest that moral intuition is not really learnable reported that they would hire people based on their personal dispositions, such as personality and moral character, rather than their skills and abilities (e.g., M2, M6), meaning those managers prioritize the hiring of individuals with desirable virtues over those with specific skills, believing that certain personal dispositions are integral for responsible decision-making and behavior.

Individual Personal Dispositions Are Influenced by and Developed Through Increased Human-AI Interaction Some knowledge workers suggested that the personal dispositions of individuals are influenced through their interaction with AI technologies. For instance, in the context of recruiting professionals, AI could foster objectivity in knowledge workers' decision-making (H3). This is because AI's neutrality in evaluating each situation based on equal criteria could rub off on them, influencing their moral assumptions and moral values: As one HR professional stated, "As the evaluation of applicants gets more objective through AI, you also start to avoid looking at the photos of applicants to make a decision and instead check only qualifications. I think that, in this respect, more objectivity through AI is a good thing" (H3, p. 10). Likewise, some argued that "most people question [AI]" (M5, p. 5) or "check [AI's] outputs by doing research" (D5, p. 6–7), which can develop their metaskills when reflecting on "What should I do with data? What should I instead not do with it?" (D5, p. 10).

While both perspectives are legitimate, in the end, an individual's personal disposition and training may be mutually enriching. One salesperson's statement illustrates this: "A mindset, you cannot simply train or learn it – it is instead something intrinsic, maybe arising when you are getting familiar with specific AI technologies and increasing your affinity … through learning by doing" (S2, p. 9).

For personal disposition to develop, organizations aim to encourage a learning culture of errors, implying that the teams share responsibility (M6, S2). As one interviewee suggested what is a essential resource for individuals in organizations working with AI responsibly: "great tolerance of failing … to fail often but learn fast" (S2, p. 16). By promoting a learning culture that embraces errors, knowledge workers are encouraged to take ownership of mistakes without fear of negative consequences from management (e.g., M6, S2). It can also promote ethical dialogue among different professionals (R2) around what is considered right or wrong in various tasks, encouraging reflection and discussion on the underlying reasoning (S2).

4.2 The Need for Human-Centered Aspects of AI Literacy Arises

It is notable that our interviewees, having provided different use cases, had different perspectives concerning which aspects would become relevant in human-AI interactions. Some highlighted that socio-cultural aspects (41.64%), such as communicating and creative thinking, rather than technical aspects, are perceived as becoming increasingly relevant for responsible human-AI interaction, especially when considering user communication through and with generative AI applications. In contrast, developers highlighted the increased complexity of AI models and stressed the importance of developmental (63.64%), critical (33.33%), and functional aspects (31.25%) for those responsible for deployment of AI technologies within business and society, implying the need for a more profound technical understanding on the part of leaders, managers, and executives who drive AI implementation strategies. Likewise, educators focused on functional (31.25%) and physical (33.33%) aspects to better integrate AI and robotics into existing curricula. This shows that different stakeholders hold different views, depending on the AI artifact, with respect to what is essential for responsibly interacting with AI, impacting their "acting responsibly," which we elaborate on in the following.

AI's Increased Complexity Requires a More Profound Technical Understanding AI was reported to gain increased autonomy and be used for tasks that can have an impact on professionals. That is why our interviews suggest that individuals should have objectives that go beyond blindly following AI and should reflect upon the input they provide AI, which requires a certain level of technical understanding. For instance, "Chat-GPT [has] a relatively simple and generic interface, [and so] the competence to assess or understand that not everything the thing says is correct [is a] minimum requirement" (D1, p. 4). This becomes particularly relevant when interacting with smart devices, in which AI's activities are not directly linked to prompts made by the human user (D1).

One salesperson explained what would be considered a minimum requirement for responsibly interacting with AI: "I should have a high level of competence in the field of statistics … The thing is, you probably needed that already a few years ago when you were dealing with [AI models]. Today, I can just somehow use AI tools out of the box, acquire them somewhere within an overall software package, and not even really know what's happening in the background. So, depending on the use case, it would actually be necessary to take a close look at how the AI works behind the scenes." (S4, p. 11). The salesperson added an example about assessing people's creditworthiness: "It's no longer just about creditworthiness in six categories, like it was maybe decades ago. Now, when assessing creditworthiness, I believe 80 or 90 characteristics are easily taken into account. It would be preferable that if I rely on this score, I agree with the criteria being used" (S4, p. 11). This shows that increased accessibility and usability of AI technologies may lead to easy usage of such assistance, but awareness of how the code works is also required when aiming to deal with AI responsibly.

AI's Increased Usability Requires Less Technical Understanding but Increased Domain Knowledge and Communication Skills While the growing complexity of AI necessitates a more profound technical understanding, the enhanced usability of generative AI technologies was also reported to demand fewer technical aspects from users, with the focus instead on social and creative skills – depending on the use case and type of AI.

In the context of using chatbots, for instance, some interviewees suggested that collaborating with AI responsibly requires increased communication skills (e.g., S2, D3). Users are required to utilize inclusive language to responsibly influence the output of AI tools (H3). As one interviewee explained, "I only have an influence on what comes out through the words I use. And depending on how precise I am in my description, I have different [outputs], and it's up to me to help shape them" (H3, p.1). This is why AI may even require improvement of communication skills, as one developer argued: "Making perfect prompts becomes more relevant, so what criteria do we need for the prompts that we put in there to get the quality that we need?" (M6, p. 3–4). Another interviewee supported this, stating, "[When] I interact with an AI-supported system, I should also just allow myself fewer spelling mistakes for the sake of simplicity, for example, or to get to the point more quickly" (S2, p. 6). A salesperson experienced an enhancement of communication skills, reporting "I use different generative AI tools [and] I just notice [that] there is also a certain learning effect for me now. Depending on what information I feed a particular tool, the answers are reasonably useful" (S4, p. 5).

One example of the increased relevance for domain knowledge was provided by a salesperson from a startup that has designed an app that analyzes images of dogs to predict their mood and needs, offering actionable suggestions for owners such as "you should go for a walk" (S6, p. 7) The app is intended to address the knowledge gap of some dog owners, as "there are indeed people who are completely unable to recognize how the animal is feeling" (S6, p.7). The salesperson emphasized that the app is designed to be as user-friendly as possible, requiring no technical skills or understanding of the model. However, the salesperson acknowledged the potential risks, noting that if the app says "the dog is fine, you don't need to go to the vet, and then the dog dies – that would, of course, be truly terrible" (S6, p.8). This highlights the ongoing need for user domain knowledge to guarantee responsible interactions, even if the AI is designed to compensate for a lack of domain knowledge.

Overall, we conclude that AI's increasing complexity necessitates technical skills to comprehend and manage the sophisticated algorithms and data processes that drive its functionality, particularly on the part of developers. Conversely, the growing usability of generative AI in particular has significantly reduced the need for technical skills, allowing more knowledge workers to use AI tools with minimal understanding of the underlying mechanisms – often requiring only basic prompting knowledge. This shift, however, places greater emphasis on domain knowledge: in order to use generative AI responsibly and purposefully (i.e., to avoid misleading or irrelevant results), users must be able to formulate inputs as concretely and contextually as possible, and critically reflect on and adapt the output to their specific subject matter. For example, a marketing professional using a generative AI tool to draft campaign slogans does not need to understand the model's architecture, but must be able to judge whether the suggestions align with brand tone, target audience, and compliance guidelines (M6).

Combining the findings, we suggest that balancing technical aspects with domain knowledge in the sense of a critical mindset and strong communication capabilities is essential to interact with AI responsibly and, thus, to foster the "acting responsibly" of individuals. However, our findings also indicate that not all AI literacy aspects apply equally to every professional role, as each use case demands a distinct combination of competencies. This emphasizes the importance of context and the type of AI in shaping AI literacy requirements. Also, given that required skills vary significantly across roles – for example, between developers and managers – role- and domain- specific training initiatives are viewed as both necessary and effective (e.g., M6, H3). This further emphasizes the need for knowledge workers to recognize their shared responsibility, particularly in contexts where their skill levels differ.

4.3 Ethical Literacy Should be Considered

Our interviews reveal that AI literacy is particularly influenced by ethical aspects that were reported as critical for fostering responsible human-AI interaction. Notably, most of our codes about abilities required for responsible human-AI interaction can be linked to ethical aspects (45.16%), while fewer pertain to data literacy (27.42%), algorithmic literacy (9.68%), digital literacy (6.45%), and others (11.29%). Based on these findings, we argue that having only certain abilities linked to ethical aspects, such as critical reflection, would not be enough to guarantee responsible interaction with AI. Rather, we would argue from the interview data that we require *ethical literacy*, which involves reflecting various ethical viewpoints, understanding underlying ethical principles, and recognizing the moral values of different communities.

For instance, our interviews highlighted the scenario of an AI-driven recruitment system used to screen job applicants (e.g., H1, H5). As an example, one interview (H1) suggests that an AI specialist with strong AI literacy may possess a detailed understanding of how an algorithm processes applications – how it weighs different variables, identifies patterns, and makes recommendations. Further, the specialist might also recognize the potential biases embedded in the system due to historical inequalities in the training data (H1), which reflects an awareness that falls under the ethical aspects of AI literacy. Both are required, however, since technical expertise without knowledge about ethical principles alone is insufficient (M6). Without ethical literacy, the specialist may fail to grasp the broader societal implications of these biases (R1) or critically reflect on whether automating hiring decisions aligns with fundamental principles of fairness and human dignity (M2). They might acknowledge that certain groups are disadvantaged, but there remains a risk that they rationalize this as an acceptable trade-off for efficiency, overlooking human rights concerns on a more systemic, meta level (D3). Moreover, knowledge workers need to recognize that moral values and ethical expectations surrounding AI applications differ across societies, as an AI-driven hiring system deemed appropriate in one cultural context may be considered deeply unethical in another (D3).

Therefore, people who may be highly AI literate but lack ethical literacy can also use AI irresponsibly. For instance, knowledge workers who can exploit system loopholes for personal gain could be considered highly AI literate in a technical sense, but their lack of ethical awareness of potential harm to others and their non-compliance with given laws and norms (linked to feeling responsible) undermine responsible human-AI interaction. Thus, we conclude that ethical literacy is crucial for fostering responsible human-AI interaction, as it contributes to "being responsible" by providing knowledge about ethical assessments and roles. Based on our interviews, we can derive two different perspectives on how ethical literacy intersects with AI literacy, discussed below.

Ethical Literacy can be Perceived as a Prerequisite for AI Literacy One perspective that emerged in the interviews suggests that ethical literacy is foundational for AI literacy. Knowledge workers were reported to need a profound understanding of ethical behavior before engaging with AI technologies. For instance, it was suggested that AI developers require ethical literacy to avoid ethical dilemmas in a system's design and to build norm-compliant systems, as programming skills alone, without ethical literacy, would not guarantee responsible AI development (M6). As "building such systems requires certain skills to address ethical issues within the system's architecture well before they manifest during user interactions" (M6, p. 15). One developer suggested that ethical considerations become particularly relevant when AI's output impacts knowledge workers: "Ethical knowledge is crucial for those responsible for AI system outputs that make predictions affecting human lives" (D5, p. 10). Concerning this, one manager recommended that "organizations should define their own understanding of ethics in general before considering AI ethics" M6, p. 12).

Although those examples could imply that ethical literacy is necessary primarily for AI designers, our interviews indicate that user ethical literacy is equally important to prevent misuse. One interviewee, in this context, pointed to how AI can facilitate breaking into IT systems, "as AI makes it easier for someone to be a hacker with little experience" (D6, p. 6) compared to previous technologies. This shows, while AI lowers the barriers to entry for interacting with technology, it may simultaneously increase the risk of unethical use when lacking ethical considerations. This example further illustrates that, in certain cases, AI literacy alone (effectively using the AI system) may be insufficient for ensuring the responsible use of AI technologies. "A basic understanding of ethical values like equality, inclusion" (S5, p. 8) was reported to be required to mitigate the risk that users manipulate the technology for personal gain, potentially leading to misuse if ethical literacy is lacking (S5). Absent ethical literacy, knowledge workers who exploit AI loopholes for personal gain and do not feel responsible for the outcomes fail to recognize that such actions can harm others and have legal ramifications (S3, p. 18). In this regard, ethical literacy can serve as a safeguard against misuse and harm to others by clarifying rules and consequences before the interaction. From this perspective, ethical literacy can be seen as a prerequisite to AI literacy.

AI Literacy can be Perceived as a Prerequisite for Ethical Literacy Some interviewees suggested that a certain level of AI literacy is necessary to recognize and address ethical issues. Understanding the complexities and underlying mechanisms of AI technologies was reported as crucial for individuals to responsibly manage AI's unintended consequences (e.g., M4, H1) and, thereby, develop their ethical literacy. Without a foundational level of AI literacy, recognizing responsibility issues was perceived as challenging (e.g., R1, R3, R4).

Particularly when decisions are based on AI recommendations, we suggest that decision-makers must first understand AI mechanisms, which then informs their ethical literacy in making responsible decisions. As one interviewee stated, "An AI can't recognize a person's value … It might suggest someone for a management position, but this person could mistreat employees, as AI cannot assess a narcissist's behavior. AI might use facial recognition to analyze word choice, but it cannot conduct a full assessment" (M6, p. 10). Being aware of AI's functioning can, thus, be seen as a foundation for knowledge workers' ethical literacy, which is then required for deciding whether the context is applicable for using AI. As another interviewer said, "I would not hire a receptionist through AI because I hire based on charisma and personality, which makes knowledge workers feel comfortable. This might differ when hiring a software developer, where the AI could be more suitable for assessing programming skills" (H1, p. 8).

These two perspectives illustrate that ethical literacy is essential to responsibly develop and interact with AI systems, and recognizing ethical issues requires a basic understanding of AI's functioning (linked to AI literacy), highlighting the need for multi-literacy. More precisely, some organizations view ethical awareness as a prerequisite for the responsible use of AI, while others emphasize the importance of developing ethical competence through experiential learning, particularly once foundational technical skills, such as programming, are in place. Since AI progress is rapidly evolving, the findings combined suggest that achieving responsible human-AI interaction requires that knowledge workers, organizations, and society have a certain baseline of moral values that are more important than technical knowledge: "You don't necessarily need a deep technical understanding of AI … rather, you need an understanding of the impact that AI can have" (R2, p 8). This implies, while technical knowledge in human-AI interaction can be acquired and refined through continuous learning, individuals must possess certain personal dispositions as moral values that underpin and promote responsible engagement with AI.

4.4 Various Factors Influence AI Literacy Development Across Different Analysis Levels

Our interviews indicate that several factors influence whether and how AI literacy can be fostered to ensure responsible human-AI interaction. While those influencing factors should not be considered as components of AI literacy, they need to be considered when conceptualizing AI literacy to answer the question of what shapes AI literacy for responsible interactions of knowledge workers with AI. As illustrated in the theoretical background (see Section 2.1), AI literacy can be analyzed on several levels. In our empirical data, however, we identified influencing factors at the individual level (micro-level, 47.47%), organizational level (meso-level, 37.74%), and societal level (macro-level, 14.79%) that influence how knowledge workers' AI literacy can develop and thus needs to be considered when holistically conceptualizing AI literacy for responsible human-AI interaction. These influencing factors could enhance AI literacy by facilitating or fostering upskilling mechanisms or diminish it through deskilling mechanisms when interacting with AI. Interestingly, most factors influencing deskilling reported were situated at the micro-level, whereas most factors that were suggested to influence upskilling were identified at the meso- or macro-level, which we explain in the following.

Deskilling is Often Influenced by Factors at the Micro-Level Our analysis highlights that increased usability, easy access, and human-like and intuitive design of AI technologies can decrease the need for AI literacy for effective interaction. Several interviewees noted that when AI systems are easy to use and understand, knowledge workers can feel less need to develop or apply certain AI literacy abilities (e.g., D6, R4, M4, S2). Specifically, AI's personalized and human-like communication, coupled with its immediate output in natural human language, can lead to a tendency to "unlearn how to question things" (D2, p. 6). However, this may undermine a responsible human-AI interaction when unintended consequences are considered. While human-like AI may not free individuals from being responsible for outcomes, it may lead knowledge workers to act less responsibly in their interactions with AI. As one interviewee observed, this may lead to excuses such as "we can't do anything about it; the system said so …" (H1, p. 10). The opacity of data processing behind AI outputs may exacerbate this issue, making critical reflection difficult (e.g., R5) and challenging to act responsibly through deskilling.

This issue was particularly evident in our interviews when it came to using generative AI applications, in which knowledge workers can interact with AI easily using natural language (e.g., M1, S2, D3). While social aspects of AI literacy – such as communication and critical aspects in evaluating outputs – become increasingly significant in this context, individuals may unlearn writing creative texts on their own (e.g., D1). As one knowledge worker explained: "If every company now starts using ChatGPT to contact applicants or customers, then of course the variety in how it's done will likely be rather limited. That means you no longer stand out" (D1, p. 10). In contrast, for instance, discussion about AI-based drones for error detection emphasized the importance of technical aspects for correct operation (M5). This shows that the type of AI technology may serve as a critical influencing factor that impacts AI literacy development at the individual level.

Another deskilling moderator at the micro-level could be the trust users place in AI technologies based on misleading perceptions of AI (R1). One researcher noted that "many people anthropomorphize AI systems and overestimate them," leading to overtrust in AI's capabilities and the mistaken belief that AI can perform tasks as effectively as knowledge workers (e.g., R1). This overtrust can inhibit the development of critical abilities to challenge AI outcomes. As one manager warned, "I see a big danger that people will question results less because of the easy way of using generative AI" (M1, p. 6). Thus, we suggest that overtrust in AI and the high usability and human-likeness of AI technologies, both micro-level moderators, can lead to deskilling and thus potentially reduce AI literacy and negatively impact responsible human-AI interaction.

Upskilling is Often Influenced by Factors at the Meso- and Macro-Levels Our interviews revealed culture-dependent factors at the meso-level that can lead to upskilling, enhancing AI literacy for responsible human-AI interaction. For instance, one manager noted, "The more technical an organizational unit, the more critically employees view AI compared to those working in marketing, who approach AI more playfully or hedonistically" (M3, p. 5). This suggests that department culture may influence whether AI technologies are applied and, consequently, whether new skills can be acquired through interacting with AI. A culture of distrust in data and novel technologies, in contrast, can hinder upskilling within organizations (M5) – except when individuals already have high AI literacy and independently use AI in opposition to the organizational culture. This was illustrated by one manager, who stated, "I analyzed data at home to get insights but presented the findings at work as if they were based on gut feeling to get things through" (M5, p. 3). As for overcoming such distrust, one manager suggested that fostering a critical and open-minded work culture is essential for the responsible deployment of AI within organizations (e.g., M2), particularly given the work culture's impact at the individual level (micro-level).

At the macro-level, our interviews further highlighted that societal moral values (e.g., R2), national resources for AI innovation (e.g., R3), and the level of AI maturity within a country (e.g., D3) may serve as key factors moderating upskilling that enhance AI literacy for responsible human-AI interaction. Specifically, adult education (D1, M6) and a sense of social duty (R2) were identified as important. Regulatory frameworks at the macro level (such as the AI Act for AI regulation) also define responsibilities (e.g., S3, D7, R1) and therefore shape "being responsible" in human-AI interactions. One developer emphasized the need to leverage AI opportunities to promote inclusivity: "We have to use AI's opportunities to include people who didn't have the opportunity before, especially [through] text-to-speech or speech-to-text, so that all individuals can interact with others" (D3, p. 7).

Organizations recognize the need to critically reflect on potential deskilling that could undermine responsible human-AI interaction and understand that addressing these influencing factors across different levels is essential for fostering the responsible use of AI technologies (e.g., M1, H1).

To address this, some propose conducting targeted audits to identify which competencies remain essential for responsible AI use and which may become less relevant (e.g., R2), for instance, through AI's increased usability (D1). Given that required skills vary significantly across roles – for example, between developers and managers – role-specific training initiatives are viewed as both necessary and effective (e.g., M6, H3). Also, several interviewees further suggested that gaps in specific AI literacy dimensions – such as domain knowledge – can be mitigated through collaboration with subject-matter experts. As one salesperson explained, that is why "we enter a co-creation phase together with the client" (S2, p. 6).

4.5 Rethinking the Concept of AI Literacy

As visualized in Fig. 2, our findings suggest that the concept of AI literacy requires reconsideration when aiming for responsible human-AI interaction, particularly in light of four key insights. Figure 3 provides further detail, based on the descriptive results of our interviews, illustrating that certain AI components gain in relevance and certain factors need to be considered when shifting from only interacting with AI efficiently to human-AI interaction that is truly responsible. The interviews thus help us to better understand what shapes AI literacy for (ir)responsible interactions of knowledge workers with AI and provide valuable insights for AI literacy conceptualizations.

First, concerning *building blocks*, we suggest from the findings that personal dispositions are foundational to responsible human-AI interaction, as they shape how knowledge workers perceive and assume responsibility for outcomes involving AI. Responsibility gaps can emerge when such dispositions are lacking, potentially undermining responsible decision-making in AI-supported environments. These dispositions are not static; they evolve through ongoing interaction with AI systems, highlighting the dynamic nature of human-AI engagement. Regarding *literacy aspects*, there is a growing need – as AI becomes more powerful – for human-centered aspects to ensure responsible use and oversight. Simultaneously, the increasing usability of AI systems reduces the need for deep technical expertise but raises the importance of domain-specific knowledge and communication skills. With respect to *related literacies*, ethical literacy emerges as a critical component of responsible AI interaction and is often viewed as a prerequisite for effective AI literacy. Conversely, acquiring AI literacy can also serve as a foundation for developing ethical reasoning in AI contexts, suggesting a reciprocal relationship. The combination of technological and non-technological literacies – particularly digital, data, and ethical – has a stronger impact on responsible AI use than any single literacy

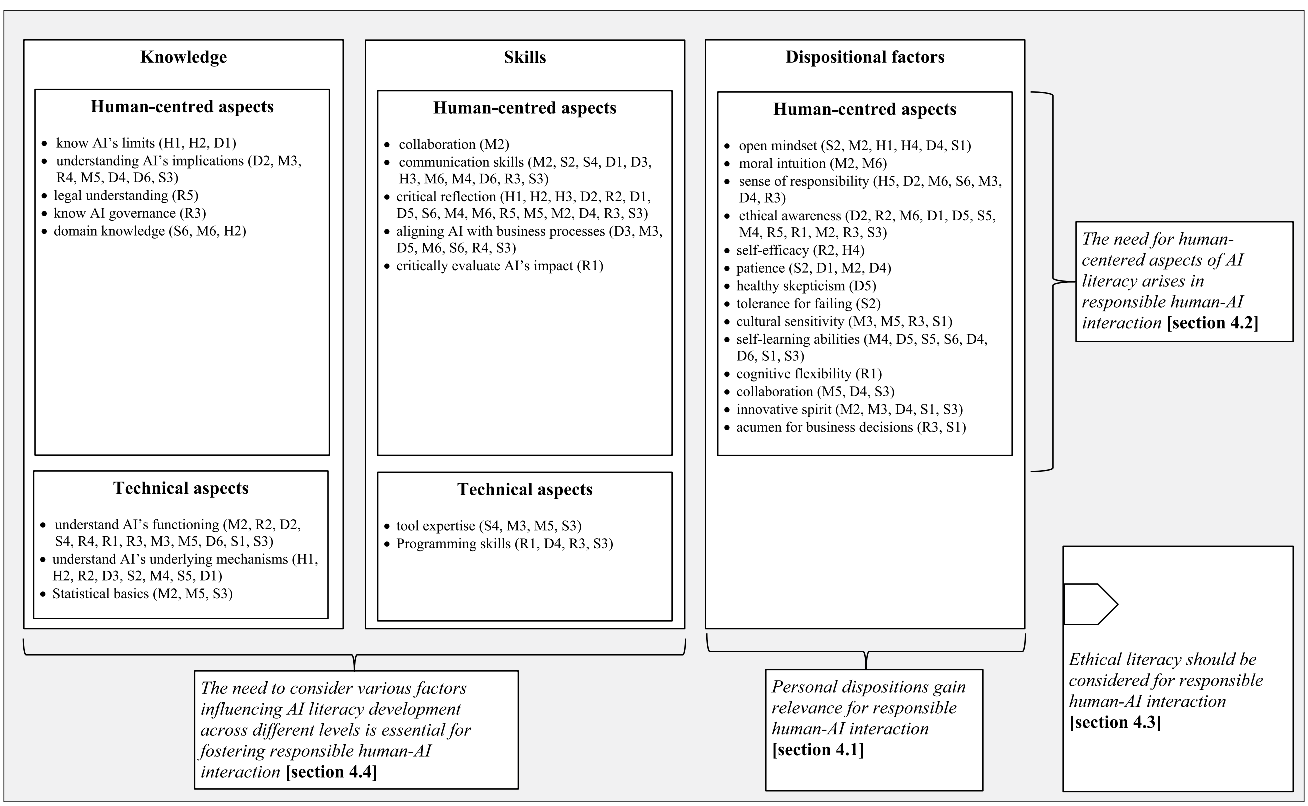

Fig. 3 Connections between the data and the four key findings

alone. When considering *different analysis levels* of AI literacy, the phenomenon of deskilling, particularly driven by micro-level factors such as overreliance on user-friendly AI systems, underscores the importance of addressing skill retention and development across individual, organizational, and systemic levels.

5 Discussion

In this section, we present the theoretical and practical implications derived from our study findings. Table 2 is an overview synthesizing the key insights discussed above, serving as the foundation for our propositions and the corresponding recommendations.

As discussed in our theoretical background, we assert that the assignment of responsibility is legitimized through two interconnected dimensions: individuals' ability to navigate specific situations (linked to *acting responsibly*) and the expectations tied to their professional roles (linked to *being responsible*). We argue that alignment between abilities and roles, what we term the role–ability fit, is essential for fostering genuinely responsible collaboration between humans and AI systems. Neglecting this alignment risks misunderstandings, inefficiencies, and even irresponsible AI use. However, our interviews challenge this assumption by revealing that such misalignment is, in fact, common in practice.

To avoid misalignment and inform organizational management, we discuss how certain problems may challenge responsible human-AI interactions with respect to *being* responsible and *acting* responsibly with AI, and suggest four future research propositions that need further investigations (Section 5.1). With respect to the practical implications, we provide recommendations for organizational strategies that may help manage human-AI interaction more responsibly (Section 5.2). We end the discussion with limitations (Section 5.3).

Table 2 Synthesis of key findings, derived propositions, and practical recommendations

Identified problems	Findings and tensions [Section 4]		Propositions [Section 5.1]	Recommendations [Section 5.2]
The *responsibility problem*: Being responsible requires an understanding of shared responsibility	Personal dispositions gain relevance for responsible human-AI interaction [Section 4.1]	Personal dispositions are a prerequisite for responsible interaction with AI Individuals' personal dispositions are influenced by and developed through human-AI interaction	Knowledge workers' personal dispositions influence how responsible they feel for outcomes of their interactions with AI; lacking certain dispositions can lead to responsibility gaps	Establish a common sense of shared responsibility among knowledge workers, each having individual personal dispositions, by fostering ethical dialogue on the right and wrong uses of AI in different situations and for different tasks and discuss the reasons
	The need for human-centered aspects arises in responsible human-AI interaction [Section 4.2]	AI's increased complexity requires a more profound technical understanding AI's increased usability requires less technical understanding but increased domain knowledge and communication skills	The interplay between technical aspects and domain-specific knowledge influences responsible human-AI interaction, with varying importance depending on AI systems and task context; this challenges the alignment of responsibilities with individual capabilities	Conceptualize AI literacy as a "toolbox" and understand it as a flexible framework that can be adapted to various human-AI interaction contexts fostering a sense of shared responsibility
The *skilling problem*: Acting responsibly requires an understanding of multi-literacies	Ethical literacy should be considered for responsible human-AI interaction [Section 4.3]	Ethical literacy can be perceived as a prerequisite of AI literacy AI literacy can be perceived as a prerequisite for ethical literacy	The integrated development of technological and non-technological literacies exerts a greater influence on fostering responsible human-AI interaction than the advancement of any individual literacy in isolation	Recruit for moral values, drive for continuous learning, and focus on organizational training that aims to strengthen these, rather than training only in AI-related knowledge and hard skills
	The need to consider various factors influencing AI literacy development across different levels is essential for fostering responsible human-AI interaction [Section 4.4]	Deskilling is often influenced by factors at the micro-level Upskilling is often influenced by factors at the meso- and macro-levels	AI's increased user-friendliness leads to deskilling, with individuals relying less on their own abilities, thus diminishing the skills needed for acting responsibly in human-AI interaction	Implement targeted and role-specific AI literacy training by assessing the most critical abilities required for different professional roles and fostering learning from one another

5.1 Theoretical Contributions: How Certain Problems may Challenge Responsible Human-AI Interaction

This section discusses problems derived from our findings that can challenge responsible human-AI interaction. We discuss these findings in relation to our theoretical background, proposing that responsible human-AI interaction requires alignment between *being responsible* and *acting responsibly* to guarantee what we framed as the *role-ability fit*. We address problems related to knowledge workers' responsibilities in human-AI interactions (*being responsible*) and those related to knowledge workers' ability to act responsibly in these interactions (*acting responsibly*). As illustrated below through the four propositions, those problems may influence the management of human-AI interaction, for which we provide managerial guidance as practical implications in Sect. 5.2.

5.1.1 The Responsibility Problems: Being Responsible Requires an Understanding of Shared Responsibility

While *being* responsible depends on accountabilities assigned per duty and defined per role (Hamilton & Hagiwara, 1992), there can be certain tensions in practice, as our interviews suggest, and whether individuals assume responsibility depends significantly on their personal dispositions [see Section 4.1]. Human-AI interaction involves multiple knowledge workers collaborating directly or indirectly with AI, with points of contact before, during, and after AI usage (Heyder et al., 2023). Given this complexity, our empirical findings highlight a greater emphasis – compared to existing AI literacy frameworks – on personal dispositions such as moral values. These dispositions appear to play a critical role in fostering knowledge workers' willingness to assume responsibility, particularly in situations where lines of accountability are blurred – for example, when no individual is formally designated as responsible or when individuals do not feel accountable for the outcomes of human-AI interactions, an occurrence similarly noted in previous studies (Mayer et al., 2020; Passlack et al., 2024).

Accordingly, our findings address the prevailing ambiguities surrounding responsibility among the various knowledge workers involved in the development, deployment, use, management, or education of AI systems. While it is argued that AI should be entrusted with final decision-making, given its perceived potential to be less error-prone (e.g., S3), our findings also reveal concerns that knowledge workers may become less inclined to assume responsibility when interacting with AI systems – particularly when they lack the AI literacy necessary to fully understand how such systems function (e.g., D4, H1). Some argue that even developers no longer understand the algorithms, as AI models' complexity may lead to greater opacity concerning how the system generates results and can lead to blind following by users (e.g., H1). The results further indicate a diffusion of responsibility: for instance, developers may view users as responsible for ensuring ethical interaction with AI, whereas users often assume that the AI itself will operate ethically. Thus, future studies would be required to explore how personal dispositions such as patience and moral values can be systematically integrated into AI literacy training and education. Research could examine how these character traits can be cultivated and measured in various organizational settings and how they contribute to responsible AI implementation and management.

We propose:

> **Proposition 1**: *Knowledge workers' personal dispositions influence how responsible they feel for outcomes of their interactions with AI, while lacking certain dispositions can lead to responsibility gaps*.

As AI becomes more advanced, powerful (Berente et al., 2021), and capable of causing more damage if misused (e.g., M3), some knowledge workers perceive that users bear a greater degree of responsibility for its use compared to earlier, less-sophisticated technologies (e.g., D1, S4). In other words, the advanced capabilities of AI require a heightened awareness and accountability on the part of those who utilize it. While some argue that more complex AI models necessitate deeper technical understanding (e.g., R1, D4), others suggest that increased usability reduces the need for technical expertise, shifting the emphasis instead toward domain knowledge and communication skills [see Section 4.2]. A lack of technical understanding can hinder individuals' ability to comprehend the underlying code, which may be essential for making informed decisions relevant to responsible AI use. Conversely, possessing technical expertise without sufficient domain knowledge limits one's ability to assess whether a model's functioning – though technically understood – is appropriate within a specific context where domain-specific insight is crucial (e.g., S6).

In addition, when roles are ill-defined or responsibilities are ambiguously distributed, it can lead to uncertainties and misalignment between required and actual capabilities, hindering an appropriate role-ability fit. For instance, our interviews lead us to suggest that everyone bears a certain level of responsibility and that different knowledge workers are involved in the process of improving AI technologies and have ethical concerns (e.g., S3, M6), given the subjective nature of ethics and moral assumptions. Further studies are needed to better understand how combinations of technical proficiency and domain-specific knowledge contribute to responsible AI interaction. Research could examine the conditions under which either type of expertise becomes more critical, and how interdisciplinary skill sets affect individuals' ability to detect, interpret, and respond to ethical challenges arising from AI deployment. Otherwise, lines of responsibility can be blurred (Giermindl et al., 2022), thereby undermining individuals' confidence in their role expectations. We derive the following proposition:

Proposition 2: *The interplay between technical aspects and domain-specific knowledge influences responsible human-AI interaction, with varying importance depending on AI systems and task context; this challenges the alignment of responsibilities with individual capabilities*.

5.1.2 The Skilling Problems: Acting Responsibly Requires an Understanding of Multi-Literacies

Acting responsibly in human-AI interaction presupposes the necessary capabilities, yet there can be certain tensions in practice flowing from whether individual skills are enough or require deeper knowledge. Concerning this, some findings indicate that possessing individual ethical skills, such as critical reflection, may be insufficient on its own to ensure responsible use. In contrast, we derive from the findings that ethical literacy emerges as an essential prerequisite for responsible human-AI interaction, as AI literacy alone would not account for responsible interactions with AI [see Section 4.3]. We propose that ethical literacy equips individuals with an understanding of human rights and the ability to navigate conflicting moral values when unintended negative consequences arise. It is essential to prevent inequalities that result from norm-compliant behavior, such as through the misuse of AI or discrimination through data biases (e.g., M3, D6). Consequently, we conclude that ethical literacy and AI literacy are dependent, and both are required for responsible human-AI interaction.

This leads us to suggest that responsible human-AI interaction must focus on the multi-literacies required for enabling individuals to act responsibly. As an example, while a developer may possess a high level of AI literacy with respect to its functional aspects, the concept of multi-literacy suggests that developers would also need ethical literacy to develop AI responsibly and inform their AI literacy. Ethical literacy is about being aware that there are different normative positions with respect to how ethics and morality can be interpreted in general. We differentiate it from the ethical aspects of AI literacy, which pertain specifically to the ability to recognize and navigate ethical conflicts within AI interactions, such as understanding issues of bias, fairness, and transparency in algorithmic decision-making, as suggested by prior research (Ng et al., 2021). While further empirical investigation is necessary to explore these connections in depth, the data generally support the importance of a multi-literacy approach in achieving responsible human-AI interaction. Thus, research is needed to examine the role of non-technological literacies within AI-related contexts, particularly ethical literacy, by reflecting on the concept of multi-literacy, with different literacies influencing each other mutually. We propose:

Proposition 3: *The integrated development of technological and non-technological literacies exerts a greater influence on fostering responsible human-AI interaction than the advancement of any individual literacy in isolation*.

Other challenges regarding skill development became evident when it comes to *acting* responsibly in human-AI interaction. While there was a consensus that AI increases the number of tasks that knowledge workers are capable of and thus upskills them (e.g., S3, M6, M3, S2), practitioners observed situations that suggest knowledge workers lose certain skills, which may negatively affect their ability to act responsibly (e.g., M1, R1, D2). The problem, therefore, is to determine the main influences on human-AI interaction, leading to upskilling or deskilling that may negatively affect knowledge workers' ability to act responsibly.

Our findings emphasize the importance of examining the interdependencies between various influencing factors at individual, organizational, industrial, and societal levels as the alignment – or lack thereof – of individual values, technological factors, and cultural norms across these levels can impact the skilling of the workforce, thus, responsible human-AI interactions [see Section 4.4]. Therefore, misalignment among these factors can result in irresponsible action, while alignment can promote responsible behavior associated with *acting responsibly*. As the results show, some interviewees suggested upskilling, in that individuals increasingly reflect on decisions and critically reflect on their own opinions when interacting with AI (e.g., M3). Likewise, the research shows that the use of AI may increase knowledge workers' critical reflection skills when analyzing AI's output (Hemment et al., 2023; Passlack et al., 2025). This results from seeing AI as a second and less-subjective opinion. However, this would require that AI has no biases that can foster unintended, irresponsible outcomes. In contrast, interviewees suggested that increased ease of use of AI systems means fewer skills are required to interact with AI, which can, in turn, deskill knowledge workers (e.g., M1, R1, D2) and impede responsible acting. The accessibility and easy usability of AI may sometimes demotivate users from trying to investigate how an AI works, since little understanding is required to interact with that AI (e.g., D6, R4). This can be aggravated by the fact that over-trust in AI can hinder critical reflection, given that users expect AI to have a high degree of accuracy and correctness (e.g., S3). Thus, future research could focus more on the interdependencies between different factors that may influence knowledge workers' upskilling and deskilling, such as conducting a cross-cultural comparison. Such investigations could also consider AI technologies' explainability and user-friendliness, or explore how users' values influence their engagement with AI artifacts differently (e.g., in a responsible or irresponsible manner) in different cultures. We propose:

> **Proposition 4**: *AI's increased user-friendliness leads to deskilling, with individuals relying less on their own abilities, thus diminishing the skills needed for acting responsibly in human-AI interaction*.

5.2 Practical Implications: How Organizations may Strategically Foster Responsible Human-AI Interaction

The interview findings further reveal practical implications with respect to how organizations may address the problems that can challenge fostering responsible human-AI interaction. We elaborate on these practical implications in the following and provide four recommendations for organizations that aim to introduce human-AI interaction effectively and responsibly.

5.2.1 Addressing the Responsibility Problems

Concerning the *responsibility* problem, our findings highlight that knowledge workers require a certain level of morality to address the responsibility gap. Given that human-AI interaction can have implications beyond fulfilling a certain task, several knowledge workers' literacies that influence human-AI interaction or that are influenced by its consequences must be considered, as also suggested by Carolus et al. (2023). Bringing diverse and interdisciplinary knowledge workers together when deciding upon AI strategies (as suggested by e.g., R2) in organizations is also required to make decisions that are aligned with ethical ideologies and moral values, which can differ between individuals and thus affect their sense of shared responsibility.

While developers should not rely solely on user moral values to ensure the responsible use of their AI technologies, users indeed bear a certain responsibility for the outcomes that result from their interactions with AI. AI interaction involves multiple stakeholders who collaborate with AI at different points, such as developers designing AI, managers implementing AI, or policymakers regulating AI, suggesting a process view of AI literacy. This is better illustrated by literature suggesting that human-AI teams "are together embedded in an encompassing organizational system, with boundaries and linkages to the broader system context and task environment" (Kozlowski & Ilgen, 2006, p. 79).

Each stakeholder requires different but complementary literacy components. Thus, dialogue among different knowledge workers and departments is required (e.g., R2), also supported by literature suggesting critically examining and clarifying shared roles and responsibilities at all levels in AI governance (e.g., Cañas, 2022). Consequently, we recommend:

> **Recommendation 1**: *Establish a common sense of shared responsibility among knowledge workers, each having individual personal dispositions, by fostering ethical dialogue on the right and wrong uses of AI in different situations and for different tasks and discussing the reasons*.

Moreover, as the interviews revealed, responsible human-AI interactions are influenced by diverse factors and are contingent on knowledge workers' use cases, making AI literacy a dynamic concept and leading to uncertainties in skill requirements. Thus, understanding AI literacy as a "toolbox" provides a flexible framework that can be adapted to various human-AI interaction contexts. We propose that understanding AI literacy as a toolbox implies that each use case requires a unique combination of specific aspects and building blocks, and is related to other literacies and influenced by factors across different analysis levels. There can be certain interdependencies between components; for instance, only the combination of ethical aspects and development aspects would account for a responsible human-AI interaction. For instance, ethical literacy and critical reflection on AI's impact should be prioritized in high-stakes decision-making tasks such as medical AI applications or legal AI advisors (e.g., R1). Conversely, other literacies gain greater importance in creative AI applications, such as generative AI for content creation, which are more closely tied to social interaction and communication (e.g., D1, H3). Theoretical models of AI literacy should, therefore, integrate these dynamic combinations rather than treat AI literacy as a static, one-size-fits-all construct.

This aligns with previous quantitative investigations on AI literacy in which measurement items of AI literacy are closely linked to the investigation context and the underlying technology being used (e.g., Kandlhofer et al., 2016; Lin et al., 2020; Ng et al., 2021). General scales for AI literacy, such as those of Weber et al. (2023), can be helpful for defining universal AI literacy requirements, but we suggest that they require the examination of specific AI aspects that need to be itemized in a scale dependent on specific AI tasks. Researchers may see AI literacy as a toolbox to identify relevant areas for their specific investigation cases and then look within that context at scales that already exist to combine them for a specific measurement instrument. Operationalizing the toolbox requires fostering interdisciplinary literacy development and perhaps combining measures to bridge the knowledge gaps between different stakeholders. As a consequence, researchers and practitioners aiming to quantify AI literacy should explore empirical applications of the toolbox across various stakeholder groups. We therefore suggest:

> **Recommendation 2**: *Conceptualize AI literacy as a "toolbox" and understand it as a flexible framework that can be adapted to various human-AI interaction contexts in the sense of shared responsibility*.

5.2.2 Addressing the Skilling Problems

Concerning the *skilling problem*, the findings suggest that knowledge workers require both AI literacy and ethical literacy. However, whether knowledge workers possess ethical literacy depends on their ability to reflect critically upon outcomes of human-AI interaction, which depends on their personal dispositions, such as their motivations, moral values, and sense of responsibility.

Some knowledge workers may have certain personal dispositions that help or motivate them to critically reflect on outcomes based on their moral values. As the findings suggest, certain moral values can be fostered, and ethical literacy can be improved to some extent through training, but perhaps not in the same way as training in knowledge or hard skills. Thus, our interviewees advise hiring "the right employees" by searching for those who bring such moral values to the organization. This could mean that hiring decisions should be based more on applicants' moral values, implying ethical literacy, than on hard skills, as also suggested in the literature (e.g., Watson et al., 2021).

Further, there is a need for continuous learning and training (e.g., Chao et al., 2021; Jaiswal et al., 2022). Since AI technologies are continually developing, certain technical skills can become outdated quickly. Thus, knowledge workers need to possess a drive for continual learning. Consequently, the findings suggest that managers need to reconsider their recruiting and personnel skilling strategies when searching for new employees for human-AI interaction, which leads to the following recommendation on how to deal with the skilling problem in organizations:

> **Recommendation 3**: *Recruit for moral values, drive for continuous learning, and focus on organizational training that aims to strengthen these, rather than training only in AI-related knowledge and hard skills*.

While organizations, educators, and policymakers face the challenge of limited resources (Mom et al., 2019), it is crucial to focus on developing the most relevant abilities for specific roles, avoiding deskilling of abilities relevant to responsible human-AI interaction, and allocating resources strategically. Rather than adopting a one-size-fits-all approach, organizations should tailor AI literacy initiatives to the needs of different knowledge workers to maximize impact. Understanding the concept of AI literacy as a toolbox can help in conducting targeted skill development. AI literacy programs should foster interdisciplinary collaboration between different stakeholder groups, enabling them to share knowledge and experiences. Rather than aiming for universal AI literacy, organizations and governments can leverage transactive memory systems that emphasize "who knows what" rather than "everyone knows everything" (Wegner, 1987). Also, organizations can foster role-specific training (M6, H3) and discussions where different stakeholders with diverse abilities are involved in AI development (Asatiani et al., 2020). This may help distribute cognitive labor effectively by structuring knowledge-sharing networks in which individuals specialize in different areas of expertise while remaining aware of the expertise of others to collaborate. Therefore, our recommendation is:

> **Recommendation 4**: *Implement targeted and role-specific AI literacy training by assessing the most critical abilities required for different professional roles and fostering learning from one another*.

5.3 Limitations

This work has some limitations that point to future research directions.

First, our analysis does not aim to deliver a comprehensive overview of all aspects of AI literacy. Rather, its core purpose is to offer a fresh perspective on how the concept of AI literacy should be rethought, aiming for responsible human-AI interaction. We advocate for moving beyond a purely efficiency-driven approach and instead highlight the need for AI literacy to foster responsible interaction by considering unintended outcomes and inequalities. This broad understanding emphasizes that knowledge workers must be equipped not only with technical know-how but also with the competence to navigate AI systems in ways that are ethically responsible and attuned to the specific contexts in which they operate. For future research, it could be relevant to investigate in more detail and more specific use cases to reveal more practical implications in specific contexts.

Moreover, future research could explore how the role-ability fit varies across different AI application contexts, industries, and organizational settings to examine mechanisms through which organizations can foster the role-ability fit.

Second, the empirical results are restricted to five groups of knowledge workers; however, lawyers and other legal practitioners may also be relevant stakeholder groups when considering literacy for responsible human-AI interaction. Given the initial insights into different use cases in which teaming knowledge workers and AI occurs, future research could enrich the discussion by involving stakeholders from the public domain (government, law) and specific industries. In addition, the progress of AI is widely discussed in the media and academic discourse, which may lead to certain AI narratives that influence individuals' thinking about human-AI interaction. Future longitudinal research could capture the impact of AI developments on what are seen as the skills required for responsible human-AI interaction.

Third, a frequently raised limitation of qualitative research is its restricted generalizability, as the inherently subjective perspectives of interview participants can pose challenges in extending the findings to wider populations (Sarker et al., 2013). To address this, we encourage future research to examine the propositions put forward in our study through quantitative approaches and across diverse domains, use cases, and AI systems. We position our findings as a conceptual contribution aimed at rethinking AI literacy in the context of fostering responsible human-AI interaction.

6 Concluding Comments

The adage "with great power comes great responsibility" applies today as the widespread use of increasingly (semi-) autonomous AI applications at work and in daily life leads to novel human-AI interaction. By analyzing the current literature, we highlight the relevance of rethinking conceptualizations of AI literacy that go beyond enhancing the efficiency and performance of human-AI interactions aimed at fostering abilities to achieve responsible human-AI interaction. By relying on 28 interviews, we aim to increase our understanding of what shapes AI literacy for responsible interactions of knowledge workers with AI.

Our qualitative study contributes to IS research by providing empirical insights into different use cases of human-AI interaction by reflecting on different knowledge workers' perspectives. We illustrate that different use cases require a unique set of AI literacy components to responsibly address potential harms associated with AI while effectively harnessing its benefits. This approach also aids in identifying potential problems that could lead to the exclusion of certain groups, organizations, or nations, thereby helping to reduce the digital divide in human-AI interactions and improving overall welfare, as advocated by Alexopoulou (2024) and Celik (2023). We aim to inform future conceptualizations of AI literacy by offering insights into how the concept may be redefined and the factors that influence its development.

The study's findings highlight that responsible human-AI interaction depends significantly on personal dispositions, which influence whether individuals feel responsible for AI-driven outcomes, potentially creating responsibility gaps. It is recommended to foster a shared sense of responsibility among knowledge workers by fostering ethical dialogue about appropriate AI use across different tasks and contexts. As AI systems become more powerful and complex, a deeper technical understanding is required, while greater usability demands less technical understanding but stronger domain knowledge and communication skills. To address this, AI literacy should be conceptualized as a flexible "toolbox" adaptable to varying interaction contexts, supporting informed and ethical decision-making. Furthermore, responsible interaction with AI calls for understanding multi-literacies, emphasizing that ethical literacy and AI literacy are interdependent and should be strengthened through recruitment for moral values, continuous learning, and targeted organizational training. Finally, to counteract the risks of deskilling from increased AI usability, organizations should implement role-specific AI literacy training based on systematic assessments of critical skill needs to guarantee a role-ability fit.

Finally, we suggest that to speak of *successful* human-AI interaction, we must aim for *responsible* human-AI interaction. By providing future research directions incorporating digital responsibility discourse within AI literacy considerations, and by outlining recommendations for organizational strategies to foster responsible human-AI interaction, we hope this work offers a valuable starting point to reflect upon AI literacy for moving toward *responsible* human-AI interaction in organizations.

Appendix 1: Literature review procedure

We conducted a theoretical literature review to identify what constitutes AI literacy for human-AI interaction according to prior research and explain the initial interdependencies of identified components. A theoretical literature review is appropriate for developing conceptualizations by identifying, describing, and transforming relevant objects into a novel structure. Since theoretical reviews aim at building an explanation through a structured and systematic research process to transform constructs identified in previous work (Paré et al., 2015), the synthesis and reorganization of AI-related research ensure the development of a holistic view of the ideas of different scholars (Burton-Jones et al., 2021). MacInnis (2011) suggests synthesizing existing theory and transforming it into a novel structure in a conceptualization to “accommodate extant knowledge; explain puzzling or inconsistent findings; [and] reveal novel insights” (p. 138).

Following Templier and Paré (2018), we searched for relevant literature by searching the following terms in titles, abstracts, and keywords: “AI literacy,” “AI capabilities,” “AI abilities,” “AI competencies,” “AI knowledge,” and “AI skills.” We searched these databases: ACM Digital Library (ACM), AIS Electronic Library (AIS), Business Source Ultimatum via EBSCOhost (BSU), IEEE Explore (IEEE), JSTOR, Science Direct (SciDir), and Web of Science (WoS). Due to the topic’s novelty, we wanted to ensure that we could consider the latest relevant conference articles, so we did not restrict our search to peer-reviewed literature or specific quality criteria (e.g., rankings); we did, however, limit our search to articles published between 2017 and 2023.

Our final search, conducted in June 2023, yielded 2,683 overall hits across all databases without the use of database filter options, 1,868 hits across all databases with the use of the database filter option that excluded non-English articles automatically ($n=22$), and articles published before 2017 ($n=793$), and 1,666 unique hits after the elimination of duplicates ($n=202$). In addition to excluding non-English articles automatically, we applied further format criteria as detailed in Table 3.

We applied further relevance criteria. To increase the quality of relevance screening, we randomly chose a small subsample of the articles ($n=37$) for parallel training purposes of the coders before conducting relevance screening. The relevance criteria were revised through subsequent discussion. The 763 articles that did not fit our relevance criteria were excluded, and 37 articles remained in the final sample. Table 4 provides an overview of the relevance screening:

We also conducted backward and forward searches and checked all articles against the format and relevance criteria described above. The remaining articles were subjected to further rounds of backward and forward searches. We repeated the process until no further relevant articles could be identified. In total, we had three rounds of backward and three rounds of forward search, resulting in 118 hits. We added nine articles resulting in 46 articles as our final sample. Figure 4 is an overview of the search process based on Templier and Paré (2018).

For the systematic synthesis of our final sample, we followed a fourth-step structure as suggested by MacKenzie to avoid “poor construct conceptualization” (2003, p. 324), which can lead to misspecifications during theory development. The first step is about defining constructs of interest and the identification of similarities among groups of capabilities, competencies, and skills (representing AI literacy aspects). The second step is about synthesizing similar expressions of AI literacy aspects and their corresponding building blocks. The third concerns thinking about

Table 3 Format screening

Database	Before 2017	Non-English	Non-scientific	Incomplete	Total
Definition	*Articles being published before 1 st January 2017*	*Articles that are not completely written in English*	*Grey literature, book chapters, book reviews, dissertations, tutorials, bachelor's or master's theses, workshops, posters, letters of editors, special issues, symposiums, talks, and magazines*	*Short papers or research-in-progress papers, and extended abstracts*	-
ACM	55	0	26	17	98
AIS	30	0	25	13	68
EBSCO	159	22 (filter)	520	0	701
IEEE	266	3 (manual)	24	1	294
JSTOR	5	0	163	0	168
SciDir	55	0	11	0	66
WoS	223	2 (manual)	51	10	286
Others	-	-	-	-	-
Total	**793** (with database filter)	**22** (with database filters) **5** (manual screening)	**820** (manual screening)	**41** (manual screening)	**1,681** (total) **866** (manual screening) **815** (with database filters)

Table 4 Relevance screening

Database	No AI focus	No AI literacy focus	No human-AI interaction focus	Total
Definition	*Technologies mentioned in the articles must be characterized by a higher level of complexity and interactivity compared to previous technologies based on AI's self-learning abilities and increased autonomy, as illustrated in the introduction*	*Articles must provide dedicated contributions regarding the components of AI literacy (aspects, building blocks, or interrelations with other literacies)*	*Articles must consider both parties (human and AI teammates) being involved in human-AI interaction. Hence, articles solely focussing on the design of AI by addressing AI abilities or solely focussing on managing or enhancing human abilities without considering the intersection with AI are not included*	-
ACM	1	34	12	47
AIS	1	77	41	119
EBSCO	35	116	122	273
IEEE	0	33	27	60
JSTOR	10	23	6	39
SciDir	1	30	22	53
WoS	11	89	72	172
Others	-	-	-	-
Total	**59**	**402**	**302**	**763**

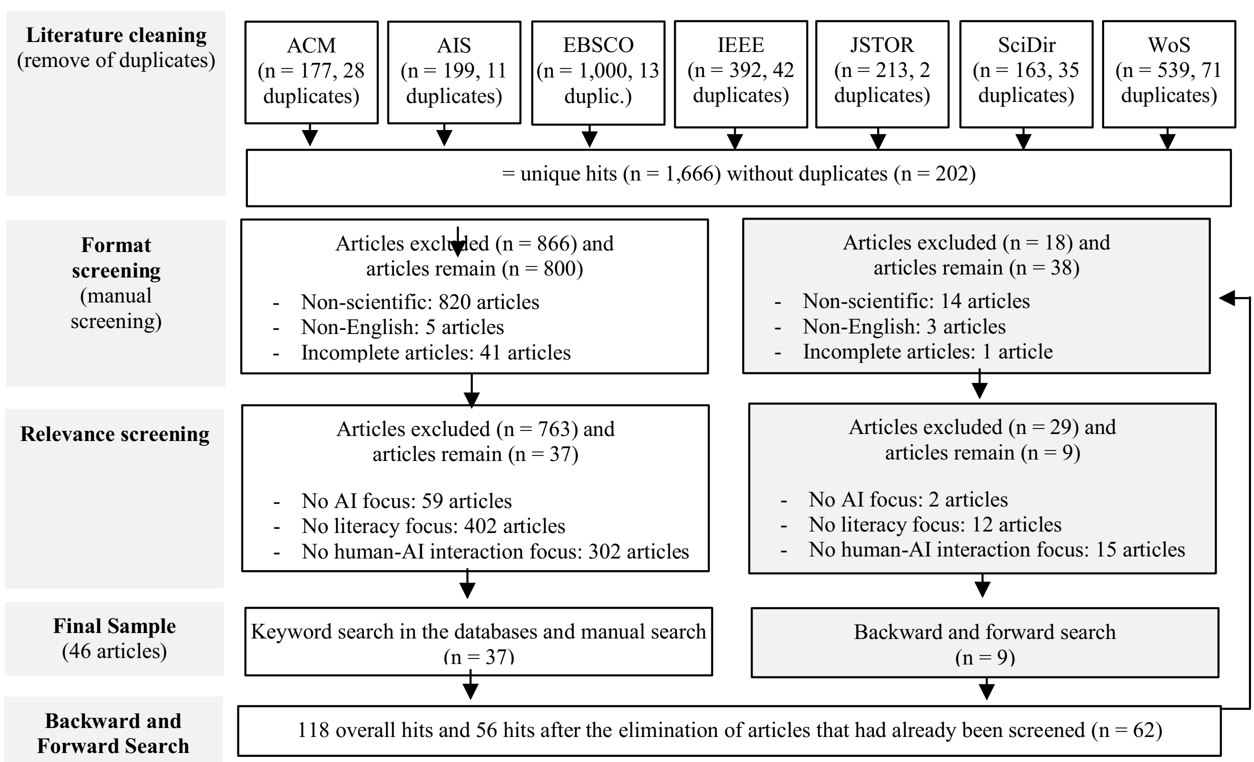

Fig. 4 Literature search process

adequate measures representing the constructs and the relation between measures and constructs. The fourth step is about the identification of relationships among constructs and the classification of those. We aimed to contribute to the design validity through our systematic and transparent description of the steps of our theoretical literature review. We aimed to increase measurement and analytical validity by having several discussion rounds amongst at least two researchers when synthesizing constructs until consensus was reached and by reporting interrater reliability using Cronbach's Alpha (McHugh, 2012). We mainly followed deductive reasoning when synthesizing constructs based on the theoretical background to increase construct and inferential validity.

Table 5 Final sample

Nbr	Autor(s)	Year	Title	Outlet	Source
1	Alekseva et al	2021	AI Adoption and Firm Performance: Management versus IT	Academy of Management	Keyword Search
2	Ali et al	2021	Children as Creators, Thinkers and Citizens in an AI-Driven Future	Computers and Education: Artificial Intelligence	Keyword Search
3	Alsheiabni et al	2019	Towards an Artificial Intelligence Maturity Model: From Science Fiction to Business Facts	Pacific Asia Conference on Information Systems (PACIS)	Keyword Search
4	Anton et al	2020	The Humans behind Artificial Intelligence – an Operationalisation of AI Competencies	European Conference on Information Systems (ECIS)	Keyword Search
5	Cetin-damar et al	2021	Explicating AI Literacy of Employees at Digital Workplaces	IEEE Transaction on Engineering Management	Keyword Search
6	Chai et al	2020	An Extended Theory of Planned Behavior for the Modelling of Chinese Secondary School Students' Intention to Learn Artificial Intelligence	Mathematics	Keyword Search
7	Carolus et al., 2023	2023	Digital interaction literacy model – Conceptualizing competencies for literate interactions with voice-based AI systems	Computers and Education: Artificial Intelligence	Keyword Search
8	Chao et al	2021	Knowledge of and Competence in Artificial Intelligence: Perspectives of Vietnamese Digital-Native Students	IEEE Access	Forward Search 1 st round
9	Casal-Otero et al	2023	AI literacy in K-12: a systematic literature review	International Journal of System Education	Keyword Search
10	Dai et al	2020	Promoting Students' Well-Being by Developing Their Readiness for the Artificial Intelligence Age	Sustainability	Keyword Search
11	Dai et al	2023	Collaborative construction of artificial intelligence curriculum in primary schools	Journal of Engineering Education	Keyword Search
12	George	2021	Redesign of an Elective Introductory Artificial Intelligence Course in a Credit-Limited Computer Science Curriculum	Journal of Computing Sciences in Colleges	Keyword Search
13	Hemmet et al	2023	AI in the Public Eye: Investigating Public AI Literacy Through AI Art	ACM Conference on Fairness, Accountability, and Transparency	Keyword Search
14	Hermann	2022	Artificial Intelligence and Mass Personalization of Communication Content— An Ethical and Literacy Perspective	New Media & Society	Keyword Search
15	Hou et al	2021	Study on the Competency Model Construction for Industrial Designers under Artificial Intelligence Technology	International Conference on Electronic Business (ICEB)	Keyword Search
16	Jaiswal et al	2021	Rebooting Employees: Upskilling for Artificial Intelligence in Multinational Corporations	The International Journal of Human Resource Management	Backward Search 2nd round
17	Kaspersen et al	2021	VotestratesML: A High School Learning Tool for Exploring Machine Learning and its Societal Implications	FabLearn Europe/MakeEd	Keyword Search
18	Kim et al	2021	Why and What to Teach: AI Curriculum for Elementary School	Conference on Innovative Applications of Artificial Intelligence	Keyword Search
19	Kong et al	2023	Evaluating an Artificial Intelligence Literacy Programme for Developing University Students? Conceptual Understanding, Literacy, Empowerment and Ethical Awareness	Educational Technology & Society	Keyword Search
20	Laupichler et al	2022	Artificial Intelligence Literacy in Higher and Adult Education: A Scoping Literature Review	Computers and Education: Artificial Intelligence	Forward Search 1 st round
21	Laupichler et al	2023	Delphi study for the development and preliminary validation of an item set for the assessment of non-experts' AI literacy	Computers and Education: Artificial Intelligence	Keyword Search
22	Leyer & Schneider	2021	Decision Augmentation and Automation with Artificial Intelligence: Threat or Opportunity for Managers?	Business Horizons	Keyword Search
23	Long & Magerko	2020	What is AI Literacy? Competencies and Design Considerations	Conference on Human Factors in Computing Systems (CHI)	Keyword Search
24	Long et al	2021	Co-Designing AI Literacy Exhibits for Informal Learning Spaces	ACM Human–Computer Interaction	Keyword Search
25	Long et al	2022	Family Learning Talk in AI Literacy Learning Activities	Conference on Human Factors in Computing Systems (CHI)	Keyword Search

Table 5 (continued)

Nbr	Autor(s)	Year	Title	Outlet	Source
26	Luo et al	2023	Aladdin's Genie or Pandora's Box for Early Childhood Education? Experts Chat on the Roles, Challenges, and Developments of ChatGPT	Early Education and Development	Keyword Search
27	Markauskaiet et al	2022	Rethinking the Entwinement Between Artificial Intelligence and Human Learning: What Capabilities do Learners Need for a World with AI?	Computers and Education: Artificial Intelligence	Forward Search 1 st round
28	Mikalef & Gupta	2021	Artificial Intelligence Capability: Conceptualization, Measurement Calibration, and Empirical Study on its Impact on Organizational Creativity and Firm Performance	Information & Management (IM)	Keyword Search
29	Mikalef et al	2021	Artificial Intelligence as an Enabler of B2B Marketing: A Dynamic Capabilities Micro-Foundations Approach	Industrial Marketing Management	Keyword Search
30	Ng et al	2021	Conceptualizing AI literacy: An Exploratory Review	Computers and Education: Artificial Intelligence	Keyword Search
31	Ng et al	2022	Using Digital Story Writing as a Pedagogy to Develop AI Literacy Among Primary Students	Computers and Education: Artificial Intelligence	Keyword Search
32	Ng et al	2023	Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world	Educational Technology Research and Development	Keyword Search
33	Pinski & Benlian	2023	AI Literacy—Towards Measuring Human Competency in Artificial Intelligence	Hawaii International Conference on System Sciences (HICSS)	Forward Search 1 st round
34	Pinski et al	2023	AI Knowledge: Improving AI Delegation through Human Enablement	CHI Conference on Human Factors in Computing Systems	Keyword Search
35	Sanusi et al	2022	Investigating Learners' Competencies for Artificial Intelligence Education in an African K-12 Setting	Computers and Education Open	Backward Search 2nd round
36	Sanusi et al	2022	The Role of Learners' Competencies in Artificial Intelligence Education	Computers and Education: Artificial Intelligence	Forward Search 1 st round
37	Su & Yang	2023	Artificial Intelligence (AI) literacy in early childhood education: an intervention study in Hong Kong	Interactive Learning Environments	Keyword Search
38	Su & Zhong	2022	Artificial Intelligence (AI) in Early Childhood Education: Curriculum Design and Future Directions	Computers and Education: Artificial Intelligence	Keyword Search
39	Su et al	2022	A Meta-Review of Literature on Educational Approaches for Teaching AI at the K-12 Levels in the Asia–Pacific Region	Computers and Education: Artificial Intelligence	Keyword Search
40	Van Brummelen et al	2021	Teaching Tech to Talk: K-12 Conversational Artificial Intelligence Literacy Curriculum and Development Tools	Conference on Innovative Applications of Artificial Intelligence	Keyword Search
41	Verma et al	2022	An Investigation of Skill Requirements in Artificial Intelligence and Machine Learning Job Advertisements	Industry and Higher Education	Forward Search 1 st round
42	Wang et al	2022	Measuring User Competence in Using Artificial Intelligence: Validity and Reliability of Artificial Intelligence Literacy Scale	Behavior & Information Technology	Keyword Search
43	Watson et al	2021	Will AI Ever sit at the C-Suite Table? The Future of Senior Leadership	Business Horizons	Keyword Search
44	Yang, W	2022	Artificial Intelligence Education for Young Children: Why, What, and How in Curriculum Design and Implementation	Computers and Education: Artificial Intelligence	Keyword Search
45	Yang, S	2022	A Systematic Literature Review on the Disruptions of Artificial Intelligence within the Business World: in Terms of the Evolution of Competences	Conférence de l'AIM	Forward Search 1 st round
46	Zhao et al	2022	Developing AI Literacy for Primary and Middle School Teachers in China: Based on a Structural Equation Modeling Analysis	Sustainability	Keyword Search

Appendix 2: Overview of participants per stakeholder group

Stakeholder	Ref. ID	Position	Organization	Expertise	#employees
Recruiters & HR people (n=5)	H1	Recruiter	Technology Provider	Preselection of candidates with AI	> 135.000
	H2	Head of IT Transformation	Automotive Supplier	AI recruiting agent; autonomous manufacturing	> 30.000
	H3	Recruiter	Insurance Company	Candidate assessment with AI; Employer branding with generative AI	> 30.000
	H4	HR Consultant	Head-hunter Agency	Candidate assessment with AI	< 10
	H5	CEO	Hiring Agency	AI recruiting agent	< 50
Managers (n=6)	M1	CEO	Ad & Media Agency	Content creation with ChatGPT and Dall-E	< 50
	M2	Head of People & Culture	Insurance Company	Damage assessment with AI; AI recruiting agent	> 10.000
	M3	Marketing Manager	Renewable Energy Provider	AI drone operations; content creation with ChatGPT	< 500
	M4	CEO	Industrial Automation	AI detection in manufacturing for predictive maintenance	< 100
	M5	Board of Directors Assistance	Pharmaceutics	Data analytics for performance evaluation; digital skiing teacher	> 1000
	M6	Marketing Manager	News & Service Platform	Content creation in journalism, predictions in marketing	> 2000
Develop-ers & Data Scientists (n=6)	D1	Software Engineer	AI Software start-up	GitHub and Microsoft Copilot for programming	> 100
	D2	Software Developer	Software Company	AI-based decision support in finance	> 220.000
	D3	Data Scientist	Car Manufacturer	AI simulation and image generation; ChatGPT for information search	> 150.000
	D4	Lead Developer	Technology Provider	Smart home to optimize processes	> 300.000
	D5	Software Developer	Tax and Audit Consulting	Algorithms for predictions; GitHub and Microsoft Copilot for programming	> 300.000
	D6	IT Security Developer	Manufacturing comany	AI bots used for cybersecurity and threat mitigation	> 80.000
Educators & Researchers (n=5)	R1	AI analyst & Researcher	AI Research Lab	Analyse social robots in care work; robots in manufacturing	> 10
	R2	Researcher	Business Analytics Institute	Educate students on explainable AI and governance mechanisms	> 50
	R3	AI research & Lecturer	University	Anomaly detection & intelligent manufacturing	> 10
	R4	Project Lead	Institute for Vocational Training	Learning records platform that supports personal-ized studying	> 20
	R5	Lecturer & Researcher	University	Mood detection through face analysis	> 10
AI provid-ers & sales personnel (n=6)	S1	Product Owner	Medical Technology Services	Smart Manufacturing & Anomaly Detection through data analytics	> 300.000
	S2	Sales Lead	Technology Provider	Programming with GitHub Copilot	> 300.000
	S3	Practice Director	AI Software Start-up	anomaly detection in manufactoring	> 100
	S4	Innovation Architect	Venture Capital	Information search with ChatGPT; matching tool in real estate market	> 10.000
	S5	Enterprise Account Executive	Cloud Services	Fraud detection in ticket sales	> 500.000
	S6	Co-Founder	AI Startup	App that does facial rcognition of animals	> 5

Appendix 3: Semi-structured interview guide

Section	Tasks and its underlying questions
Entry	• Welcome the interviewee • Ask the interviewee to test the microphone and to switch on the camera (voluntary) • Shortly introduce the researchers and its functions • Shortly repeat the project background and aim ○ Note: The abbreviation AI stands for Artificial Intelligence. (To avoid influencing, we deliberately do not use a definition as a basis, we ask for the self-understanding in the second section of our interview.) • Explain the structure of the interview • Explain what happens with the data after the interview and explain that solely the audio will be recorded and deleted after being transcribed • Ask if there are questions regarding the process or the interview beforehand • Ask if they agree to be recorded and start the recording
i) Introduction	We start with the first block of our interview, where we would like to know some information about the interviewee's background and functions: • In what type of company or institution are you currently employed? [Context: business model, industry, and corporate culture] ○ What is the business model and vision behind it? ○ How would you describe the culture in your work environment, esp. with regard to technology use? [Attention—check: to which unit/level does the answer refer: UN vs. team] ○ What is the role of AI in the company? • What is your current position, and how long have you held it? [Assign job history & educational background] ○ What work experience did you have before your current position? • What are your current primary responsibilities? [Context: Activities] ○ Do you have responsibility for individuals? If so, for how many and to what extent? ○ Do you have responsibility for technologies (e.g., maintenance, implementation decision)? If yes, what types of technologies and to what extent?
ii) AI definition and use case(s)	• What is your understanding of AI? Please briefly describe what impulses, examples, or characteristics come to mind when you hear the buzzword AI ○ How would you differentiate between Human Intelligence and AI? • Please describe at least one example where AI-based technologies are used for private tasks in daily life or working situations in your daily business. Please clearly describe the task, its purpose, the type/group of individuals that conduct this task in cooperation with AI-based technologies, and the situation in which the task is executed [Explanation: These can be AI-based systems with which you interact directly (in the role of the person using them) or with which others (e.g., employees, students, customers) interact and with which you are therefore more indirectly involved (e.g., responsibility, implementation, training). These can be AI-based technologies controlled by the organization (i.e., initiated by the subordinate), as well as the uncontrolled and selective use of such technologies.] ○ Specific task of human-AI interaction ○ Purpose/Aim (possible outcome variable(s)) of human-AI interaction ○ Type of Individual/Group of People conducting the task ○ Type of the AI or the technology in which the AI is embedded ○ Situation (e.g., frequency, routinized or non-routinized task)

Section	Tasks and its underlying questions
iii) Context-specific requirements	Questions per stakeholder group: • Recruiters: ○ What can HR do to improve human-AI interaction? ○ What abilities are organizations searching for when hiring individuals to work on AI projects? ○ What abilities do recruiters need for future candidate acquisition and selection with AI? • Managers: Please describe the ideal workforce: ○ What abilities are needed from the workforce in this/those example/s to deal with AI (even though this does not represent reality)? ○ What are the minimum abilities individuals need to accomplish the underlying task in your mentioned example/s? ○ If you would need to hire someone for your specific task mentioned, for which abilities would you ask? • Developers/Data Scientists: ○ As an AI developer, what can you do to improve the human-AI interaction of later users? ○ What are the abilities developers need when designing AI or training AI? ○ What abilities do you expect from users? • Educators/Researchers: ○ What abilities does a society or state require for human-AI interaction? ○ How would you describe the future abilities of AI-literate citizens? • Sales/Product Managers: ○ What abilities do organizations require when aiming to deploy AI? ○ What are the minimum abilities organizations must have to implement AI-based technologies successfully? ○ If you would need to hire a team member in your sales team for your specific task mentioned, for which abilities would you ask? ○ How would you describe the ideal client organization for successful and responsible AI project implementation? How is their leadership team?
v) Context-specific barriers	[Explanation] The interviewee mentioned several abilities for specific situations of human-AI interaction. Now, they should describe what has been done, what is done, and what should be done (from individuals, the organization, or society) to establish or foster those abilities Questions per stakeholder group: • Recruiters: ○ What do you think hinders an individual's development of abilities needed for interaction between humans and AI? ○ What can the single employee do to foster capabilities in human-AI interaction? • Managers: ○ What do you think hinders a workforce's development of abilities needed for interaction between humans and AI? ○ What do you think hinders an organization's development of abilities needed for AI deployment? ○ What can organizations do to foster the development of relevant abilities required for deploying and using AI in organizations? • Developers/Data Scientists: ○ What do you think is hindering the development of abilities of individuals that are needed for AI development? ○ What can the developers do to foster capabilities in human-AI interaction? • Educators/Researchers: ○ What do you think hinders a society's development of abilities needed for interaction between humans and AI? ○ What can society or a state do to ensure that humans and AI-based technologies work together? • Sales/Product Managers: ○ What do you think hinders an organization's development of abilities needed for AI deployment? ○ What can organizations do to foster the development of relevant abilities required for human-AI interaction and prepare an organization for human-AI interaction?
Closing	• Stop the recording and clarify the end of the interview • Explain what will happen in the next step • Ask if there are any questions • Ask how they find the interview (feedback for researchers) • Ask for suggestions on what else should be considered in the current study, to help discover any potential incompleteness • Thank the interviewees

Appendix 4: Snapshot of coding

Part of the Conceptualization	Code	Coding Rule/Definition	Coding Example	Descriptive Statistics
Literacies	Ethical literacy	Articulate ethical viewpoints and reflect moral values	"we had discussions with the software providers on how to make sure that the AI assessment is objective. For example, the AI might reject an applicant due to a foreign name. The question is, how do we notice that? Therefore, it is important that you have this objective view somehow (dual control) and that you can take this step back to analyse what's happening there. Usually, you have it mapped through hierarchies or other decision-making policies. You can't have one person deciding alone. You have at least two humans deciding together. And maybe this can be transferred to the AI by having a technical solution for dual control within decision-making." (M2)	45.16% of 62 overall codes
	Writing literacy	Compose and read text for communication and learning	"How do I communicate a problem? [That's] important both in communication among developers and with the customer or with AI because if I can't say cleverly what my problem is, then no AI tool in the world will help me." (D1)	3.23% of 62 overall codes
	Legal literacy	Awareness of legal issues based on knowledge about law and human rights	"People can be checked at work—with or without AI. How many parcels they have delivered? How long was someone in the bathroom, and how often did someone make a break? Employee A delivered 100, and Employee B delivered 300 packages. Is it ethical or unethical to compare that? This legal situation is the same with or without AI." (M5)	8.06% of 62 overall codes
	Data literacy	Ability to collect, analyze, structure, and interpret data	"That means many people assume building the model itself is extremely demanding and requires a lot of expertise. But in fact, it's the other way around: 90% of the work lies in preparing and identifying the data, which is the decisive part." (S3)	27.42% of 62 overall codes
	Digital literacy	Ability to interact effectively with digital tools such as information and communication technologies	"The necessary prerequisite is being able to operate digital technologies, that is, having basic IT skills. You can use a smartphone, a laptop, set up an internet connection, and similar things" (R2)	6.45% of 62 overall codes
	Algorithmic literacy	understanding and appropriately utilizing algorithms	"specifically with Google—we know they're skimming something off, but we have no idea at which point something happens and what exactly is being collected. Similar to Outbrain, we don't know that at all. For me, the first step would be to understand what is going where, and at what stage anything is being transferred at all." (M6)	9.68% of 62 overall codes

The 'Ref. IDs' such as "M2" or "D1" correspond to the participants listed in Appendix 2

Appendix 5: Findings regarding building blocks and aspects

Use Cases	Ref. ID	Building blocks	Aspects
Decision-making tasks • Recruiting and pre-selection of candidates (H1, H5, M2, M6) • Candidate assessment in recruiting (H2, H3, H4)	• H1 • H2 • H3 • H4 • H5	Personal dispositions	• open mindset (M2, H1, H4) • moral intuition (M2) • sense of responsibility (H5, D2) • ethical awareness (D2, R2, M6) • self-efficacy (R2, H4)
• Decision-support in financial consulting (D2) • Explainable AI (R2)	• M2 • D2 • R2	Knowledge	• know AI's limits (H1, H2) • understanding AI's implications (D2) • understand AI's functioning (M2, R2, D2, R2) • understand AI's underlying mechanisms (H1, H2, R2) • domain specific knowledge (H2)
		Skills	• collaboration (M2) • communication (M2) • critical reflection (H1, H2, H3, D2, R2)
Creation and information tasks • Content creation (H3, D1, D3, M1, M3, M6) • Information search (D3, S4) • Programming with generative AI (D1, D5, S2)	• H3 • M1 • M3 • M6 • D1 • D3	Personal disposition	• patience (S2, D1) • open mindset (S2) • healthy skepticism (D5) • moral intuition (M6) • tolerance for failing (S2) • cultural sensitivity (M3)
	• D5 • S2 • S4	knowledge	• know AI's limits (D1) • understanding AI's underlying mechanism (D3, S2) • understanding AI implications (M3) • domain specific knowledge (M6)
		skills	• communication skills (S2, D1, D3, H3, M6) • aligning AI with business proccesse (D3, M3)
Prediction tasks • Data analytics and algorithmic prediction (D1, D5, M6)	• M4 • M6 • D1 • D5	Personal disposition	• self-learning abilities (M4, D5, S5, S6) • ethical understanding and moral values (M6, D1, D5, S5, M4, R5) • sense of responsibility (M6, S6)
• Fraud detection (S5) • Predictive maintenance (M4) • Mood detection and facial recognition (S6, R5)	• R5 • S5 • S6	knowledge	• legal understanding (R5) • understand AI's underlying mechanism (M4, S5, D1) • domain specific knowledge (S6)
		Skills	• critical reflection (D1, D5, S6, M4, M6, R5) • communication skills (M4, M6, D1) • aligning AI with business proccesse (D5, M6, S6)
Optimization tasks • Data analytics and performance evaluations (M5) • Smart home (D4) • AI drone operations (M3) • Anomaly detection and damage assessment (M2, R3, S1, S3) • Bots for threat mitigation (D6)	• M2 • M3 • M5 • D4 • D6 • R3 • S1 • S3	Personal disposition	• openness (M2, D4, S1) • innovative spirit (M2, M3, D4, S1, S3) • patience (M2, D4) • ethical awareness (M2, R3, S3) • sense of responsibility (M3, D4, R3) • cultural sensibility (M5, R3, S1) • collaboration (M5, D4, S3) • self-learning ability (D4, D6, S1, S3) • acumen for business decisions (R3, S1)
		Knowledge	• knowing AI governance (R3) • tool expertise (M3, M5, S3) • statistical basics (M2, M5, S3) • understanding AI's implications (M3, M5, D4, D6, S3) • understand AI's basic functioning (M3, M5, D6, R3, S1, S3)

Use Cases	Ref. ID	Building blocks	Aspects
		Skills	• programming skills (D4, R3, S3) • communication skills (D6, R3, S3) • aligning AI with business processes (S3) • critical reflection (M5, M2, D4, R3, S3)
Physical tasks • Healthcare robots in elderly care (R1)	• R1	personal disposition	• cognitive flexibility (R1) • ethical awareness (R1)
• Robots in manufacturing for material handling (R1)		knowledge	• understand AI's functioning (R1)
		skills	• programming skills (R1) • critically evaluate AI's impact (R1)
Communicative and supportive tasks	• R4 • S4	knowledge	• know AI's functioning (S4, R4) • understanding AI's implications (R4)
• Chatbots for customer support • Teaching agents (R4, M5) • Matching algorithms for customer preferences (S4)		skills	• tool expertise (S4) • communication skills (S4) • aligning AI with business processes (R4)

The 'Ref. IDs' correspond to the participants listed in Appendix 2

Acknowledgements The authors would like to express their gratitude for the guidance and support from the editorial team.

Authors' Contributions Conceptualization: N.P., T.H., O.P.; methodology: N.P., T.H.; research: N.P., T.H.; conducting interviews: N.P., T.H.; data analysis: N.P., T.H.; writing – original draft preparation: N.P., T.H.; writing – review and editing: N.P., T.H., O.P.; supervision: O.P.; project administration: N.P.

Funding Open Access funding enabled and organized by Projekt DEAL. No funding was received.

Data Availability Not applicable.

Declarations

Ethics Approval and Consent to Participate All interview participants took part in the study voluntarily, and all ethical standards were adhered to during the conduct and analysis of the interviews.

Consent for Publication All authors have read and agreed to the final version of the manuscript.

Competing interests The authors do not have any conflicts or interests to declare.

References

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Quarterly, 25*(1), 107–136. https://doi.org/10.2307/3250961

Alexopoulou, S. (2024). Paradigm shift: Exploring the impact of digital technologies on the welfare state through a systematic literature review. *Social Policy and Administration*. https://doi.org/10.1111/spol.13054

Alexopoulou, S., Åström, J., & Karlsson, M. (2022). The grey digital divide and welfare state regimes: A comparative study of European countries. *Information Technology & People, 35*(8), 273–291. https://doi.org/10.1108/ITP-11-2020-0803

Ali, S., DiPaola, D., Lee, I., Sindato, V., Kim, G., Blumofe, R., & Breazeal, C. (2021). Children as creators, thinkers and citizens in an AI-driven future. *Computers and Education: Artificial Intelligence, 2*, Article 100040. https://doi.org/10.1016/j.caeai.2021.100040

Alsheiabni, S., Cheung, Y., & Messom, C. (2019). Towards an artificial intelligence maturity model: from science fiction to business facts. *Pacific Asia conference on information systems (PACIS)*.

Anton, E., Behne, A., & Teuteberg, F. (2020). The Humans Behind Artificial InᵀᴱᴸIligence – An Operationalization Of AI Competencies. In *European Conference on Information Systems (ECIS)*.

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., & Benjamins, R. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115.

Asatiani, A., Malo, P., Nagbøl, P. R., Penttinen, E., Rinta-Kahila, T., & Salovaara, A. (2020). Challenges of explaining the behavior of black-box AI systems. *MIS Quarterly Executive, 19*(4), 259–278.

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior, 45*(2), 159–182. https://doi.org/10.1002/job.2735

Bawden, D. (2008). Origins and concepts of digital literacy. *Digital Literacies: Concepts, Policies and Practices, 30*, 17–32.

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Special issue editorial: Artificial intelligence in organizations: Current state and future opportunities. *Journal of the Association for Information Systems, 22*(2), 10.

Benlemlih, M., & Bitar, M. (2018). Corporate social responsibility and investment efficiency. *Journal of Business Ethics, 148*, 647–671.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly*. https://doi.org/10.25300/MISQ/2021/16274

Boichak, O., Canzonetta, J., Sitaula, N., McKernan, B., Taylor, S., Rossini, P., ..., Stromer-Galley, J. (2019). Beyond the Medium: Rethinking Information Literacy through Crowdsourced Analysis. In T. X. Bui (Ed.), *Proceedings of the 52nd annual hawaii international conference on system sciences*. University of Hawaii at Manoa Hamilton Library ScholarSpace.

Bradley, J. H., Paul, R., & Seeman, E. (2006). Analyzing the structure of expert knowledge. *Information and ManagemeNt, 43*(1), 77–91. https://doi.org/10.1016/j.im.2004.11.009

Burton-Jones, A., Butler, B. S., Scott, S., & Xu, S. X. (2021). Next-generation information systems theorizing: A call to action. *MIS Quarterly, 45*(1), 301–314.

Cañas, J. J. (2022). AI and ethics when human beings collaborate with AI agents. *Frontiers in Psychology, 13*, 836650.

Carolus, A., Augustin, Y., Markus, A., & Wienrich, C. (2023). Digital interaction literacy model–conceptualizing competencies for literate interactions with voice-based AI systems. *Computers and Education: Artificial Intelligence, 4*, Article 100114.

Cecez-Kecmanovic, D., Galliers, R. D., Henfridsson, O., Newell, S., & Vidgen, R. (2014). The sociomateriality of information systems. *MIS Quarterly, 38*(3), 809–830.

Celik, I. (2023). Exploring the determinants of artificial intelligence (AI) literacy: Digital divide, computational thinking, cognitive absorption. *Telematics and Informatics, 83*, Article 102026.

Cetindamar, D., Kitto, K., Wu, M., Zhang, Y., Abedin, B., & Knight, S. (2022). Explicating AI Literacy of Employees at Digital Workplaces. *IEEE Transactions on engineering management*, 1–14. https://doi.org/10.1109/TEM.2021.3138503

Chao, P.-J., Hsu, T.-H., Liu, T.-P., & Cheng, Y.-H. (2021). Knowledge of and competence in artificial intelligence: Perspectives of Vietnamese digital-native students. *Ieee Access, 9*, 75751–75760. https://doi.org/10.1109/ACCESS.2021.3081749

Constantinescu, M., Voinea, C., Uszkai, R., & Vică, C. (2021). Understanding responsibility in responsible AI. Dianoetic virtues and the hard problem of context. *Ethics and Information Technology*. https://doi.org/10.1007/s10676-021-09616-9

Crewswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). SAGE.

Dalkir, K. (2013). *Knowledge management in theory and practice*. Routledge.

DiSessa, A. A. (2018). Computational literacy and \textquotedblthe big picture\textquotedbl concerninc computers in mathematics education. *Mathematical Thinking and Learning, 20*(1), 1–43.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Eshleman, A. (2014). *Moral responsibility*. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy*. Stanford University. https://plato.stanford.edu/archives/fall2019/entries/moral-responsibility/

Evans, J. A., & Foster, J. G. (2011). Metaknowledge. *Science, 331*(6018), 721–725. https://doi.org/10.1126/science.1201765

Ferguson, L. W. (1960). Ability, interest, and aptitude. *Journal of Applied Psychology, 44*(2), 126–131.

Ferguson, M. J., Hassin, R., & Bargh, J. A. (2008). Implicit motivation: Past, present, and future. *Handbook of motivation science*, 150–166.

Frezza, S., Daniels, M., Pears, A., Cajander, Å., Kann, V., Kapoor, A., McDermott, R., Peters, A.-K., Sabin, M., & Wallace, C. (2018). Modelling competencies for computing education beyond 2020: A research based approach to defining competencies in the computing disciplines.In *Proceedings Companion of the 23rd Annual ACM conference on innovation and technology in computer science education*, 148–174. https://doi.org/10.1145/3293881.3295782

Gabric, D., & McFadden, K. L. (2001). Student and employer perceptions of desirable entry–level operations management skills. *American Journal of Business, 16*(1), 5–60. https://doi.org/10.1108/19355181200100005

Garrison, D. R., Cleveland-Innes, M., Koole, M., & Kappelman, J. (2006). Revisiting methodological issues in transcript analysis: Negotiated coding and reliability. *The Internet and Higher Education, 9*(1), 1–8. https://doi.org/10.1016/j.iheduc.2005.11.001

Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2022). The dark sides of people analytics: Reviewing the perils for organisations and employees. *European Journal of Information Systems, 31*(3), 410–435. https://doi.org/10.1080/0960085X.2021.1927213

Gilster, P. (1997). *Digital literacy*. John Wiley & Sons.

Hamilton, V. L., & Hagiwara, S. (1992). Roles, responsibility, and accounts across cultures. *International Journal of Psychology, 27*(2), 157–179. https://doi.org/10.1080/00207599208246873

Hemment, D., Currie, M., Bennett, S. J., Elwes, J., Ridler, A., Sinders, C., Vidmar, M., Hill, R., & Warner, H. (2023). AI in the Public Eye: Investigating Public AI Literacy Through AI Art. In *Proceedings of the 2023 ACM conference on fairness, accountability, and transparency*, 931–942.

Hermann, E. (2022). Artificial intelligence and mass personalization of communication content—An ethical and literacy perspective. *New Media & Society, 24*(5), 1258–1277. https://doi.org/10.1177/14614448211022702

Heyder, T., & Posegga, O. (2021). Extending the foundations of AI literacy. In *International conference on information systems (ICIS)*.

Heyder, T., Passlack, N., & Posegga, O. (2023). Ethical management of human-AI interaction: Theory development review. *The Journal of Strategic Information Systems, 32*(3), Article 101772. https://doi.org/10.1016/j.jsis.2023.101772

Holford, W. D. (2022). An ethical inquiry of the effect of cockpit automation on the responsibilities of airline pilots: Dissonance or meaningful control? *Journal of Business Ethics, 176*(1), 141–157.

Horneber, D., & Laumer, S. (2023). Algorithmic accountability. *Business & Information Systems Engineering, 65*(6), 723–730.

Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. *The International Journal of Human Resource Management, 33*(6), 1179–1208. https://doi.org/10.1080/09585192.2021.1891114

Kandlhofer, M., Steinbauer, G., Hirschmugl-Gaisch, S., & Huber, P. (2016). Artificial Intelligence and Computer Science in Education: From Kindergarten to University. In *IEEE Frontiers in education conference (FIE)*. 1-9. https://doi.org/10.1109/FIE.2016.7757570

Kathala, K. C. R., & Palakurthi, S. (2024). AI Literacy Framework and Strategies for Implementation in Developing Nations. *Proceedings of the 2024 16th international conference on education technology and computers*, 418–422. https://doi.org/10.1145/3702163.3702449

Kegel, M., & Ghanem, L. (2024). You did that on purpose! An Investigation of the knobe effect in human-robot interactions. In *Proceedings of the 57th Hawaii International Conference on System Sciences*. https://doi.org/10.24251/HICSS.2024.088

Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological Science in the Public Interest, 7*(3), 77–124. https://doi.org/10.1111/j.1529-1006.2006.00030.x

Kunz, W. H., & Wirtz, J. (2024). Corporate digital responsibility (CDR) in the age of AI: Implications for interactive marketing. *Journal of Research in Interactive Marketing, 18*(1), 31–37.

Lankshear, C., & Lawler, M. (1987). *Literacy, schooling and revolution*. Falmer.

Laupichler, M. C., Aster, A., Schirch, J., & Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. *Computers and Education: Artificial Intelligence, 3*, Article 100101. https://doi.org/10.1016/j.caeai.2022.100101

Laupichler, M. C., Aster, A., & Raupach, T. (2023). Delphi study for the development and preliminary validation of an item set for the assessment of non-experts' AI literacy. *Computers and Education: Artificial Intelligence, 4*, Article 100126.

Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis. *Organization Science, 33*(1), 126–148.

Leonardi, P. M. (2012). *Materiality, sociomateriality, and socio-technical systems: What do these terms mean? How are they related? Do we need them?* (SSRN Scholarly Paper 2129878). https://doi.org/10.2139/ssrn.2129878

Lerner, J. S., & Tetlock, P. E. (1999). Accounting for the effects of accountability. *Psychological Bulletin, 125*(2), 255.

Lin, C. H., Wu, L. Y., Wang, W. C., Wu, P. L., & Cheng, S. Y. (2020). Development and validation of an instrument for AI-Literacy. *3rd Eurasian conference on educational innovation (ECEI)*.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *CHI conference on human factors in computing systems* (pp. 1–16). https://doi.org/10.1145/3313831.3376727

Long, D., Teachey, A., & Magerko, B. (2022). Family Learning Talk in AI Literacy Learning Activities. *Proceedings of the 2022 CHI conference on human factors in computing systems*, 1–20.

Luke, C. (1997). *Technological Literacy: Research into Practice Series No. 4*. National Languages and Literacy Institute of Australia.

MacInnis, D. J. (2011). A framework for conceptual contributions in marketing. *Journal of Marketing, 75*(4), 136–154. https://doi.org/10.1509/jmkg.75.4.136

MacKenzie, S. B. (2003). The dangers of poor construct conceptualization. *Journal of the Academy of Marketing Science, 31*(3), 323–326.

Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2021). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower, 43*(2), 334–354.

Manca, S., Bocconi, S., & Gleason, B. (2021). "Think globally, act locally": A glocal approach to the development of social media literacy. *Computers & Education, 160*, 104025. https://doi.org/10.1016/j.compedu.2020.104025

Markauskaite, L., Marrone, R., Poquet, O., Knight, S., Martinez-Maldonado, R., Howard, S., Tondeur, J., de Laat, M., Buckingham Shum, S., Gašević, D., & Siemens, G. (2022). Rethinking the entwinement between artificial intelligence and human learning: What capabilities do learners need for a world with AI? *Computers and Education: Artificial Intelligence, 3*, Article 100056. https://doi.org/10.1016/j.caeai.2022.100056

Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics*. https://doi.org/10.1007/s10551-018-3921-3

Martini, F., & Sénéchal, M. (2012). Learning literacy skills at home: Parent teaching, expectations, and child interest. *Canadian Journal of Behavioural Science = Revue Canadienne Des Sciences Du Comportement, 44*(3), 210–221.

Matthias, A. (2004). The responsibility gap: Ascribing responsibility for the actions of learning automata. *Ethics and Information Technology, 6*(3), 175–183. https://doi.org/10.1007/s10676-004-3422-1

Mayer, A.-S., Strich, F., & Fiedler, M. (2020). Unintended consequences of introducing AI systems for decision making. *MIS Quarterly Executive, 19*(4), 239–257. https://doi.org/10.17705/2msqe.00036

Mayring, P. (2014). *Qualitative content analysis: Theoretical foundation, basic procedures and software solution*. Klagenfurt.

McHugh, M. L. (2012). Lessons in biostatistics: Interrater reliability: The kappa statistic. *Biochemia Medica, 22*(3), 359–372. https://doi.org/10.1201/b16720-37

McLean, K. (2013). Literacy and technology in the early years of education: Looking to the familiar to inform educator practice. *Australasian Journal of Early Childhood, 38*(4), 30–41. https://doi.org/10.1177/183693911303800405

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and ManagemeNt, 58*(3), Article 103434. https://doi.org/10.1016/j.im.2021.103434

Mirbabaie, M., Brünker, F., Möllmann Frick, N. R. J., & Stieglitz, S. (2022). The rise of artificial intelligence – Understanding the AI identity threat at the workplace. *Electronic Markets, 32*(1), 73–99. https://doi.org/10.1007/s12525-021-00496-x

Mom, T. J. M., Chang, Y.-Y., Cholakova, M., & Jansen, J. J. P. (2019). A multilevel integrated framework of firm HR practices, individual ambidexterity, and organizational ambidexterity. *Journal of Management, 45*(7), 3009–3034. https://doi.org/10.1177/0149206318776775

Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. *Informing Science: The International Journal of an Emerging Transdiscipline, 26*, 39–68.

Myers, M. D., & Newman, M. (2007). The qualitative interview in IS research: Examining the craft. *Information and Organization, 17*(1), 2–26. https://doi.org/10.1016/j.infoandorg.2006.11.001

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*. https://doi.org/10.1016/j.caeai.2021.100041

Ng, D. T. K., Luo, W., Chan, H. M. Y., & Chu, S. K. W. (2022). Using digital story writing as a pedagogy to develop AI literacy among primary students. *Computers and Education: Artificial Intelligence, 3*, Article 100054. https://doi.org/10.1016/j.caeai.2022.100054

Nordbye, G. H. H., & Teigen, K. H. (2014). Being responsible versus acting responsibly: Effects of agency and risk taking on responsibility judgments. *Scandinavian Journal of Psychology, 55*(2), 102–114. https://doi.org/10.1111/sjop.12111

Oeldorf-Hirsch, A., & Neubaum, G. (2023). What do we know about algorithmic literacy? The status quo and a research agenda for a growing field. *New Media & Society*. https://doi.org/10.1177/14614448231182662

Pappas, I. O., Mikalef, P., Dwivedi, Y. K., Jaccheri, L., & Krogstie, J. (2023). Responsible digital transformation for a sustainable society. *Information Systems Frontiers, 25*(3), 945–953. https://doi.org/10.1007/s10796-023-10406-5

Paré, G., Trudel, M.-C., Jaana, M., & Kitsiou, S. (2015). Synthesizing information systems knowledge: A typology of literature reviews. *Information and ManagemeNt, 52*(2), 183–199. https://doi.org/10.1016/j.im.2014.08.008

Parker, S. K., & Grote, G. (2022). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology, 71*(4), 1171–1204. https://doi.org/10.1111/apps.12241

Passlack, N., Hammerschmidt, T., & Posegga, O. (2024). It was(n't) me: Vignette experiments on managers' responsibility attribution in AI-advised decision-making. *Behaviour & Information Technology*, 1–30. https://doi.org/10.1080/0144929X.2024.2431050

Passlack, N., Gerholz, K.-H., & Schlottmann, P. (2025). Reskilling me softly: Perceived changes in students' skilling when using GenAI in Academic Research Projects. In *Proceedings of the 58th Hawaii International Conference on System Sciences*. https://doi.org/10.24251/HICSS.2025.593

Pinski, M., & Benlian, A. (2023). AI literacy—towards measuring human competency in artificial intelligence. In *Proceedings of the 56th Hawaii international conference on system sciences (Ed.)*, HICSS Proceedings 2023.

Qin, J., & D'ignazio, J. (2010). The central role of metadata in a science data literacy course. *Journal of Library Metadata, 10*(2–3), 188–204. https://doi.org/10.1080/19386389.2010.506379

Rafner, J., Dellermann, D., Hjorth, A., Veraszto, D., Kampf, C., MacKay, W., & Sherson, J. (2022). Deskilling, upskilling, and reskilling: A case for hybrid intelligence. *Morals & Machines, 1*(2), 24–39.

Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms: Toward human-AI hybrids. *MIS Quarterly, 43*(1), iii–ix.

Rana, N. P., Chatterjee, S., Dwivedi, Y. K., & Akter, S. (2022). Understanding dark side of artificial intelligence (AI) integrated business analytics: Assessing firm's operational inefficiency and competitiveness. *European Journal of Information Systems, 31*(3), 364–387.

Reddy, P., & Sharma, B. (2020). Digital literacy: A review of literature. *International Journal of Technoethics, 11*(2), 65–94.

Reinhardt, U. E. (1992). Reflections on the meaning of efficiency: Can efficiency be separated from equity? *Yale Law & Policy Review, 10*(2), 302–315.

Ridley, M., & Pawlick-Potts, D. (2021). Algorithmic literacy and the role for libraries. *Information Technology and Libraries*, *40*(2). https://doi.org/10.6017/ital.v40i2.12963

Rosenfeld, K. N. (2016). Terms of the digital age: Realities and cultural paradigms. In *Handbook of research on media literacy in the digital age* (pp. 115–144). IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-4666-9667-9.ch006

Sanusi, I. T., Olaleye, S. A., Agbo, F. J., & Chiu, T. K. F. (2022a). The role of learners' competencies in artificial intelligence education. *Computers and Education: Artificial Intelligence, 3*, 100098. https://doi.org/10.1016/j.caeai.2022.100098

Sanusi, I. T., Olaleye, S. A., Oyelere, S. S., & Dixon, R. A. (2022b). Investigating learners' competencies for artificial intelligence education in an African K-12 setting. *Computers and Education Open, 3*, Article 100083. https://doi.org/10.1016/j.caeo.2022.100083

Sarker, S., Xiao, X., & Beaulieu, T. (2013). Guest editorial: Qualitative studies in information systems: A critical review and some guiding principles. *MIS Quarterly, 37*(4), iii–xviii.

Sarker, S., Xiao, X., Beaulieu, T., & Lee, A. S. (2018). Learning from first-generation qualitative approaches in the IS discipline: An evolutionary view and some implications for authors and evaluators (part 1/2). *Journal of the Association for Information Systems, 19*(8), 752–774.

Selber, S., & Selber, S. A. (2004). *Multiliteracies for a digital age*. Southern Illinois University Press.

Smith, N., & Vickers, D. (2021). Statistically responsible artificial intelligences. *Ethics and Information Technology, 23*(3), 483–493. https://doi.org/10.1007/s10676-021-09591-1

Su, J., & Yang, W. (2023). Artificial intelligence (AI) literacy in early childhood education: An intervention study in Hong Kong. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2023.2217864

Su, J., & Zhong, Y. (2022). Artificial intelligence (AI) in early childhood education: Curriculum design and future directions. *Computers and Education: Artificial Intelligence, 3*, Article 100072. https://doi.org/10.1016/j.caeai.2022.100072

Templier, M., & Paré, G. (2018). Transparency in literature reviews: An assessment of reporting practices across review types and genres in top IS journals. *European Journal of Information Systems, 27*(5), 503–550. https://doi.org/10.1080/0960085X.2017.1398880

Trier, M., Kundisch, D., Beverungen, D., Müller, O., Schryen, G., Mirbabaie, M., & Trang, S. (2023). Digital responsibility. *Business & Information Systems Engineering, 65*(4), 463–474. https://doi.org/10.1007/s12599-023-00822-x

Trocin, C., Mikalef, P., Papamitsiou, Z., & Conboy, K. (2023). Responsible AI for digital health: A synthesis and a research agenda. *Information Systems Frontiers, 25*(6), 2139–2157. https://doi.org/10.1007/s10796-021-10146-4

Verma, A., Lamsal, K., & Verma, P. (2022). An investigation of skill requirements in artificial intelligence and machine learning job advertisements. *Industry and Higher Education, 36*(1), 63–73. https://doi.org/10.1177/0950422221990990

Wahl, M. F., & Prause, G. (2013). Toward understanding resources, competencies, and capabilities: Business model generation approach. *Entrepreneurship and Sustainability Issues, 1*(2), 67–80. https://doi.org/10.9770/jesi.2013.1.2(1)

Wang, B., Rau, Pei-Luen Patrick, & Yuan, T. (2022). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, 1–14. https://doi.org/10.1080/0144929X.2022.2072768

Watson, G. J., Desouza, K. C., Ribiere, V. M., & Lindič, J. (2021). Will AI ever sit at the C-suite table? The future of senior leadership. *Business Horizons, 64*(4), 465–474. https://doi.org/10.1016/j.bushor.2021.02.011

Weber, P., Pinski, M., & Baum, L. (2023). Toward an Objective Measurement of AI Literacy. In *PACIS 2023 Proceedings*. 60. https://aisel.aisnet.org/pacis2023/60

Wegner, D. M. (1987). Transactive Memory: A Contemporary Analysis of the Group Mind. In B. Mullen & G. R. Goethals (Eds.), *Theories of Group Behavior* (pp. 185–208). Springer New York. https://doi.org/10.1007/978-1-4612-4634-3_9

Yamaguchi, S. (2018). Changes in returns to task-specific skills and gender wage gap. *Journal of Human Resources, 53*(1), 32–70.

Yokoi, R., Eguchi, Y., Fujita, T., & Nakayachi, K. (2021). Artificial intelligence is trusted less than a doctor in medical treatment decisions: Influence of perceived care and value similarity. *International Journal of Human-Computer Interaction, 37*(10), 981–990. https://doi.org/10.1080/10447318.2020.1861763

Zamani, E., & Vannini, S. (20225). Digital policy narratives: addressing grand challenges or exacerbating digital inequalities?. *Information Technology for Development*, 1–20.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Nina Passlack Is a doctoral candidate at the Faculty of Information Systems and Applied Computer Sciences at the University of Bamberg, Germany. She holds a Master of Science in International Information Systems Management from the University of Bamberg. Her research primarily explores socio-technical issues, with a particular emphasis on responsibility attribution in human-AI interactions and the competencies necessary for the responsible use of AI.

Teresa Hammerschmidt (neè Heyder) is an affiliate member of the Department of Information Systems and Social Networks at the University of Bamberg. She completed her Ph.D. in Information Systems from the University of Bamberg in 2025. Her research primarily investigates the ethical management of human-AI interaction within organizations, with a focus on sociotechnical system theory

Oliver Posegga Is a professor at the Department of Information Systems and Social Networks at the University of Bamberg, Germany. His research focuses on social networks, digital collaboration, and the sociotechnical dynamics of hybrid media systems as well as the ethical management of AI, AI literacy, and digital responsibility.