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RESEARCH PAPER

# AI Literacy for the top management: An upper echelons perspective on corporate AI orientation and implementation ability

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**Abstract**
We draw on upper echelons theory to examine whether the AI literacy of a firm's top management team (i.e., TMT AI literacy) has an effect on two firm characteristics paramount for value generation with AI—a firm's AI orientation, enabling it to identify AI value potentials, and a firm's AI implementation ability, empowering it to realize these value potentials. Building on the notion that TMT effects are contingent upon firm contexts, we consider the moderating influence of a firm's type (i.e., startups vs. incumbents). To investigate these relationships, we leverage observational literacy data of 6986 executives from a professional social network (LinkedIn.com) and firm data from 10-K statements. Our findings indicate that TMT AI literacy positively affects AI orientation as well as AI implementation ability and that AI orientation mediates the effect of TMT AI literacy on AI implementation ability. Further, we show that the effect of TMT AI literacy on AI implementation ability is stronger in startups than in incumbent firms. We contribute to upper echelons literature by introducing AI literacy as a skill-oriented perspective on TMTs, which complements prior role-oriented TMT research, and by detailing AI literacy's role for the upper echelons-based mechanism that explains value generation with AI.

**Keywords** AI orientation · AI implementation · AI literacy · Attention-based view · Upper echelons theory

**JEL Classification** M15 · O30 · L22

## Introduction

Recent computational advancements enable a wave of artificial intelligence (AI) technologies promising to generate new value for companies by addressing many existing problems or inefficiencies, such as the automation of previously not automatable processes (Enholm et al., 2021; Shollo et al., 2022). Currently, much of this value remains unclaimed, with 70% of organizations reporting that AI delivered minimal business impact, according to a global executive study (Ransbotham et al., 2019). In the long term, however, firms without the ability to put AI to effective use will have competitive disadvantages. At least the remaining 30% of firms, according to the global executive study, have already found value-generating use cases of AI, and more use cases are continuously being developed, such as recent applications of generative AI in customer service or software development (Brynjolfsson et al., 2023; Peng et al., 2023). Hence, firms and, ultimately, their executives are urged to manage the development and adoption of AI solutions that generate new value in their particular industry and business model to remain competitive. Otherwise, they face potentially existential challenges in the future, as evidenced by prior value-unlocking technological developments that wiped out firms (e.g., Nokia or Blackberry in the smartphone industry).

Despite the importance of AI for firms, there is a lack of research and direction from information systems (IS) academics and practitioners on how executives can foster the

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development and adoption of AI that ensures continuous value generation and averts critical threats to their businesses. Upper echelons theory (UET) suggests that executives' personal characteristics have a significant influence on corporate strategy and, ultimately, how effectively firms create value (Hambrick & Mason, 1984). For instance, IS research showed that executives' willingness to challenge IT concerns depends on their IT skills (Bassellier et al., 2003). Drawing on UET, this paper investigates the promising concept of AI literacy at the level of the top management team (TMT) as a predictor for key firm characteristics that ensure value-generating AI adoption, as well as their respective firm type as a critical moderator of these relationships.

AI literacy refers to a human's holistic proficiency concerning AI that enables critical usage and evaluation of AI, as well as effective communication and collaboration with AI (Cetindamar et al., 2022; Dai et al., 2020; Long & Magerko, 2020). The share of executives within the TMT that possess AI literacy then describes the *TMT AI literacy* of the respective firm. Practitioners underscore the relevance of such a novel concept by urgently calling for more "Board Directors AI Literacy" (Gordon, 2022) and "empowering AI leadership" (World Economic Forum, 2022). Also, initial IS research identified executives' lack of AI literacy as one crucial inhibiting factor to the development and adoption of AI in firms (Yang et al., 2021). At the same time, we already know that technology, in general, is no longer a fringe topic for specific executives (Baesens et al., 2016; Bassellier et al., 2015). All executives, including the more business-oriented ones, must have a minimum level of technology literacy —it has been true for a while now that "business cannot afford technology-illiterate managers anymore" (Keen, 1991, p. 121). Despite this imperative, prior upper echelons research in the IS literature predominantly investigated the effects of the presence of individual executive roles, for example, how the presence of a chief information officer (CIO) on a firm's board affects strategic orientation toward AI (Li et al., 2021). Moreover, particularly IS-related executive roles, such as a CIO, can have significantly different responsibilities, making their role designations ambiguous (Benlian & Haffke, 2016; Haffke et al., 2016; Peppard et al., 2011). Together, this raises the question of whether the role-oriented perspective that IS research has taken so far to study (AI-related) firm characteristics for value generation is sufficient to describe adequately how top management affects these. In contrast to this predominant role-oriented perspective, this study takes a skill-oriented view by examining the AI literacy of each member in a firm's TMT—thus also shifting from the individual perspective to a team perspective.

Generating value by adopting AI in an organizational context requires firms first to identify an AI value potential (e.g., find efficiency potential in customer service processes) and then realize the respective value (e.g., set up a project to implement an AI solution that enables customer service agents to handle calls more efficiently) (Brynjolfsson et al., 2023; Gordon, 2022; Mikalef & Gupta, 2021). Identifying AI value potentials requires an organization to develop a strategic *AI orientation*, defined as a firm's overall strategic direction and goals associated with introducing and applying AI technology (Li et al., 2021). Realizing this value through concrete AI solutions necessitates, among other factors, *AI implementation ability*, defined as a firm's ability to implement IS with an AI component (Weber et al., 2022). Among different organizational resources, IS research and practice identified human resources (HR) as one of the most critical factors for successfully implementing AI, leading us to consider specifically *HR-related* AI implementation ability in this study (Brock & von Wangenheim, 2019; Roepke et al., 2000; Wamba-Taguimdje et al., 2020). Executives are urged to develop these two firm characteristics, AI orientation and HR-related AI implementation ability, which are paramount for a firm to adopt AI that is truly value-generating (Li et al., 2021; Miles & Arnold, 2017; Papagiannidis et al., 2021). A rigorous AI orientation puts AI with a specific purpose on an organization's strategic agenda, while a successful HR-related AI implementation ability, for example, given by available competent AI developers and project managers, is critical to the execution of such a strategic agenda. Accordingly, we formulate our first research question (RQ1): *How does a firm's TMT AI literacy affect its AI orientation and HR-related AI implementation ability?*

Moreover, it is crucial to note that TMTs do not act in a vacuum. When Hambrick (2007) revisited his originally proposed UET, he noted that the relationship between executives' characteristics and how firms behave could be significantly impacted (i.e., moderated) by different factors, such as the firm's type. Firm type can be seen as a common configuration of organizational resources. Therefore, this research also investigates firm type as a potential moderator of the relationship stated in RQ1 to provide a richer understanding of the proposed mechanism.

Different firm types tend to be endowed with varying configurations of organizational resources relevant to how effectively TMTs can affect AI orientation and implementation (Criscuolo et al., 2012). For example, established firms (i.e., incumbents) pursuing AI projects (e.g., FedEx Corporation, 2022) tend to have access to more (IT) resources or distribution opportunities, among other factors (Kohler, 2016). Such substantial resource endowment could help incumbents' TMTs present a more convincing AI strategy to the company owners, suggesting a high AI orientation (Baker & Nelson, 2005). Newer firms (i.e., startups) pursuing such projects (e.g., Uptake Technologies Inc., 2023) tend to have a more agile, experimental, and data-driven organizational culture as well as greater adaptability, among other factors (Davenport & Bean, 2018; Steiber & Alänge, 2020).

Such a culture might enhance the TMT's influence on firm operations because their decisions to attract AI talent spread quickly throughout the company, promoting HR-related AI implementation ability (Weber et al., 2022).

Knowing how incumbents and startups affect the TMT's influence holds significant relevance for TMTs because it offers advice on how to adjust their management approach based on the type of firm they lead. Depending on how effective TMT AI literacy influences AI orientation or HR-related AI implementation ability, executives might need to allocate their attention differently when strategizing or implementing AI. If executives know that TMT AI literacy does not effectively translate into AI orientation in their particular firm type, they could strategically invest efforts into identifying and eliminating obstacles to it. Given firm type's potential to contextualize our understanding of the basic mechanism proposed by UET (Hambrick, 2007), and its high practical relevance, we formulate a second research question (RQ2): *How does firm type (startup vs. incumbent) affect the relationship between TMT AI literacy and a firm's AI orientation and HR-related AI implementation ability?*

To answer these two research questions, we analyzed observational literacy data of 6986 executives (i.e., skills and competencies disclosed by executives via LinkedIn.com) in conjunction with firm data on AI orientation and HR-related AI implementation ability (i.e., information disclosed by firms via their annual report (10-K statement) and LinkedIn.com). Our analysis reveals that TMT AI literacy is positively associated with a firm's AI orientation and HR-related AI implementation ability. In addition, we show that AI orientation itself positively affects HR-related AI implementation ability and that it mediates TMT AI literacy's effect on HR-related AI implementation ability. Lastly, we found that firm type moderates the effect of TMT AI literacy on HR-related AI implementation ability, such that it is stronger in startup firms than in incumbent firms. Several robustness checks substantiate our findings despite the constraints of executive self-reporting.

This study makes the following contributions: (1) We introduce a skill-oriented perspective on top management teams for the AI context (TMT AI literacy) and uncover its positive effects on AI orientation and HR-related AI implementation ability. Therefore, we depart from the prevalent role-oriented perspective in upper echelons' IS research (Ding et al., 2014; Li et al., 2021) and focus on the literacy of executive teams instead of the presence of individual roles. We extend the discourse by answering the known limitations of a role-oriented approach (Haffke et al., 2016). In addition, we go beyond existing AI literacy research by considering executives in addition to users and developers (Sambasivan et al., 2021; Wang et al., 2022). (2) We introduce HR-related AI implementation ability in the upper echelons context, bridging the gap between AI value identification, achieved through AI orientation (Li et al., 2021), and AI value realization, achieved through AI implementation (Weber et al., 2022). We add to the conversations on value-generating AI adoption by elucidating TMT AI literacy's direct and indirect impact (via AI orientation) on HR-related AI implementation. (3) We develop a perspective on differences between firm types (startups vs. incumbents) in the context of upper echelons research. Drawing on the notion that UET is context-dependent (Hambrick, 2007), our study identifies firm type to contextualize the influence of TMT AI literacy on different firm characteristics. We show how startups facilitate TMT AI literacy's influence on AI implementation ability. By introducing firm type as a moderating factor, the study links AI strategy and implementation literature to broader management literature, enriching the understanding of AI adoption dynamics across diverse organizational contexts. Lastly, we derive practical implications for designing executive roles and TMTs as well as for AI management approaches based on firm type.

## Theoretical background

In the following subsection, we elaborate on the UET and the attention-based view of the firm (ABV), which forms the theoretical foundation of this study ("Upper echelons theory and the attention-based view of the firm" section). We then present related work on the principal constructs of the study: We provide background information on the emergent literature stream on AI literacy in IS research ("AI literacy" section) and review the concepts of AI orientation and AI implementation ability ("AI orientation and AI implementation ability" section). An overview of the study's constructs, including a delineation of related constructs, is available in Table 1.

### Upper echelons theory and the attention-based view of the firm

According to the UET, firms' decisions reflect how their executives ("upper echelons") perceive their environment and how much attention they pay to specific matters in their environment (Hambrick & Mason, 1984). UET's strong emphasis on managerial attention is closely related to the ABV of the firm, thus specifying the ABV for executives (Ocasio, 1997, 2011). The ABV's fundamental presumption is that a firm's behavior is determined by how it divides and channels its attention. Therefore, the ABV assumes that the more management focuses on an issue, the more resources and support it will receive, resulting in the desired outcomes for the firm. According to UET, these outcomes can be attributed to the decisions of executives and reflect their characteristics (Carpenter et al., 2016; Hambrick & Mason,

**Table 1** Overview of used and delineated constructs

| Construct | Description | Examples | Level |
|---|---|---|---|
| Foundational construct | | | |
| AI literacy | A human's holistic proficiency concerning AI that enables critical usage and evaluation of AI as well as effective communication and collaboration with AI | Heyder and Posegga (2021) and Long and Magerko (2020) | Individual level |
| Principal constructs (i.e., part of the research model) | | | |
| TMT AI literacy | The collective AI literacy of the top management team (TMT). | This research | Firm level |
| AI orientation | A firm's overall strategic direction and goals associated with introducing and applying AI technology and thus guiding AI-related strategic decisions, including AI-related investments and management practices | Li et al. (2021) | Firm level |
| (HR-related) AI implementation ability | A firm's (HR-related) ability to implement IT systems with an AI component | Mikalef et al. (2019) and Weber et al. (2022) | Firm level |
| Firm type | A typical configuration of organizational resources that enables the segmentation of firms into meaningful categories, such as startup vs. incumbent firms | Kohler (2016) and Leppänen et al. (2023) | Firm level |
| Delineated constructs (i.e., delineated from AI literacy) | | | |
| IT competence | A human's ability to use and evaluate general IT—where general IT is delineated from AI through the facets of inscrutability, autonomy, and learning (Berente et al., 2021) | Bassellier et al. (2003) | Individual level |
| AI knowledge | A human's understanding of AI—where AI literacy is delineated from AI knowledge (and other individual competence constructs) as a holistic proficiency construct that enables humans to critically evaluate and use AI compared to (only) understanding individual facts about AI | Pinski et al. (2023a) | Individual level |
| Supplementary constructs (i.e., used to support hypotheses development) | | | |
| Expertise | A characteristic of an executive that describes competence and knowledge in a particular narrowly defined field | Li et al. (2021) | Individual level |
| Power | A characteristic of an executive that describes the ability to influence others in a specific organizational setting | Hambrick (2007) | Individual level |
| Decision scrutiny | The critical appraisal and diligence from different perspectives that a team invests to make a decision | Yaniv (2011) | Firm level |

1984). Such characteristics include, for example, executives' values, perceptions, skills, or expertise (Klein & Harrison, 2007). In other words, executives' expertise (i.e., competence and knowledge in a particular narrow field) directs their attention, leading to desired outcomes (Li et al., 2021). For instance, IS studies showed that executives' willingness to challenge IT concerns and their inclination to interact with IT departments are influenced by their (general) IT skills (Bassellier et al., 2003; Bassellier et al., 2015).

More recently, Hambrick (2007) reviewed the initially formulated UET and extended their original theorizing with different factors that impact the underlying mechanism of executives' characteristics on firm decisions and outcomes. They identify managerial discretion, job demands, and executives' power as essential factors and suggest that the theorized relationship of UET becomes weaker when they are low and, respectively, stronger when they are high (Hambrick, 2007). For example, managerial discretion is influenced by different factors like firm characteristics and resources (e.g., a weak board) or environmental circumstances (e.g., industry growth), which determine the discretion an executive has on strategic decisions (Hambrick, 2007). Also, an executive's power, i.e., the ability to influence others in a specific organizational setting, can magnify the influence a particular executive has on a strategic decision.

While UET emphasizes the individual attributes of executives, many upper echelons studies focus on the composition of the board of directors, often also referred to as the top management team (TMT) (Carpenter et al., 2016). In examining the TMT, IS research has often operationalized leaders' characteristics that UET says are critical to strategic decision-making and business outcomes, such as educational background, through specific leadership roles. For example, studies associated the presence of a chief sustainability officer with more corporate social responsibility activities (Fu et al., 2019) or the presence of administrative executive roles generally (e.g., HR, finance, legal) with greater IT investments (Guadalupe et al., 2014). In the IS field, many UET-based studies focused on the roles of the chief technology officer (CTO) and chief information officer (CIO) (Benlian & Haffke, 2016). For instance, studies linked the presence of a CTO to an increase in profitability (Cetindamar & Pala, 2011) or the presence of a CIO to an improvement in information quality (Ding et al., 2014). The CIO and CTO responsibilities are often not distinct in organizations. However, if they are separated, CIOs tend to be more inwardly focused (e.g., on internal information flow), whereas CTOs tend to be more outwardly oriented (e.g., on customer information flow) (Hunts, 2021).

While the operationalization of UET via executive roles is purposeful, such a role-oriented perspective also has inevitable drawbacks (Scuik & Hess, 2022). Executive roles reflect what a firm wants to focus its attention on. However, focusing on roles neglects the unique person who assumes the respective executive role. How qualified or skilled a person is for the executive role, or how the person interprets the purpose of the executive role, might direct the intended attention in a different direction. IS-related executive roles, in particular, such as the CIO or CTO, are often ambiguously defined (Haffke et al., 2016; Peppard et al., 2011). Researchers called the CIO role “riddled with ambiguity” because they found multiple (sub)roles with significantly diverging foci of attention, such as an “Innovator CIO,” a “Utility IT Director,” or a “Facilitator CIO” (Peppard et al., 2011). Furthermore, some themes within the TMT relate to multiple executive roles, which diminishes the explanatory value of a single executive role.

To date, upper echelons research in the IS literature focusing on AI has been limited and exclusively role-oriented. Research has shown that a CIO’s presence positively affects a firm’s AI orientation (Li et al., 2021). Firms with a CIO role in their TMT incorporate AI more often into their strategic agenda than firms without a CIO (Li et al., 2021). However, the preceding discussion of role-oriented executive research poses the question of whether this relationship reveals the complete picture. Moreover, apart from CIOs’ impact on AI orientation, we still lack insights into the impact of executives on firm characteristics, such as AI implementation ability, which is critical to realizing the identified value potentials. IS research did start to deduct (non-AI-specific) skill profiles of upper echelons (Scuik & Hess, 2022). Following such prior (non-AI) research, a skill-oriented perspective on AI, i.e., AI literacy of executives or the TMT, might be a useful complement to the prevailing role-oriented perspective (Bassellier et al., 2003; Bassellier et al., 2015; Scuik & Hess, 2022). Research and practice calling for greater AI literacy in all executive roles (Gordon, 2022; Yang et al., 2021) underscore that a perspective focused on the person rather than the role would provide additional insight.

## AI literacy

Under the term “AI literacy,” a growing body of IS research has started investigating how to enable humans to use and evaluate AI (Heyder & Posegga, 2021; Pinski et al., 2023b; Yang et al., 2021). AI literacy can be described as a human’s holistic proficiency concerning AI that enables critical usage and evaluation of AI as well as effective communication and collaboration with AI (Cetindamar et al., 2022; Dai et al., 2020; Deuze & Beckett, 2022; Hermann, 2021; Long & Magerko, 2020). Rather than focusing on purely technical features of AI technology, this literature stream considers human–AI collaboration by analyzing different “features” of humans (e.g., competencies, knowledge, skill) concerning AI (Anton et al., 2020; Pinski et al., 2023a; Wang et al., 2022). In contrast to an individual competence or a certain piece of knowledge, AI literacy describes a holistic proficiency with primarily enabling character, as evidenced by the manifold human features (e.g., competencies, knowledge, skill) ascribed to AI literacy (Cetindamar et al., 2022; Dai et al., 2020; Deuze & Beckett, 2022; Hermann, 2021; Long & Magerko, 2020). Furthermore, AI literacy is distinct from self-efficacy (Bandura, 1986)—a commonly used construct in IS literature—because it describes actual human enablement and capacity to act compared to the human’s belief in their capacity to act in an AI context. In retrospect, technological “literacy” is not a new concept (Leidig & Salmela, 2020). However, due to AI’s disruption of core IS assumptions, such as functional transparency or functional consistency (Berente et al., 2021), AI literacy distinguishes itself from other technology literacy concepts, such as digital or data literacy (Eshet-Alkalai, 2004; Kerpedzhiev et al., 2020). AI’s characteristics (e.g., learning and inscrutability of machine learning applications (Janiesch et al., 2021)) enable use cases for firms requiring new literacy components, such as evaluating the business risk from an AI without functional transparency. In conceptualizing AI literacy, almost all studies include competencies, skills, and knowledge related to the social context of AI, such as the ethical judgment of AI technologies or critical assessment of AI output, in addition to technical understanding (Cetindamar et al., 2022; Ng et al., 2021; Pinski & Benlian, 2023).

Furthermore, the emergent literature emphasizes that AI literacy is a highly stakeholder-specific construct (Arrieta et al., 2020; Benlian et al., 2022; Meske et al., 2020).

Diverse groups, for example, developers, nontechnical employees, or executives, need AI literacy tailored to their specific function. The discourse is currently dominated by user- (Wang et al., 2022), student- (Steinbauer et al., 2021), or developer-oriented (Sambasivan et al., 2021) research, while executives have been largely overlooked. However, the potential impact of executives on strategic decisions and outcomes for their firms and beyond is enormous. The mandate of executives is to ensure that their firm continues to create value by extending or securing its competitive position. Such a mandate equips executives with the ability to change a firm's strategic orientation and ways of creating value, affecting not only business outcomes but also outcomes relevant to employees, customers, and society.

Assessing how AI can create value should be a top priority of an executive (Shollo et al., 2022; Wamba-Taguimdje et al., 2020). Therefore, executives' tasks include continuously assessing a firm's AI orientation and AI implementation ability, contributing to value creation (Li et al., 2021; Weber et al., 2022). Executives' tasks differ from those of other positions, requiring executives to have their own AI literacy. Among other things, executives must have a broad understanding of the entire AI process to make purposeful decisions; they do not need to know every (technical) aspect (Peifer et al., 2022). For instance, they could make decisions on the distribution of organizational tasks between human employees and AI. Making such a decision requires knowledge of the advantages and disadvantages of AI and humans in the context of specific use cases (Adam et al., 2022; Peifer et al., 2022). In summary, AI literacy of executives—and TMT AI literacy as the collective construct—has the potential to significantly affect crucial firm characteristics (e.g., AI orientation or AI implementation ability) but received little attention from IS researchers thus far.

## AI orientation and AI implementation ability

Adopting AI for successful value creation demands TMTs to perform various tasks. Two key tasks for AI adoption are establishing AI orientation and AI implementation ability. First, TMTs must identify AI value potentials and formulate a strategy to capture them while considering all stakeholders in the process (Li et al., 2021). Before adopting AI in a firm, TMTs need to understand its unique value proposition and risks in their specific use case (Shollo et al., 2022). Furthermore, they must define common objectives and evaluation standards and manage the alignment with all affected employees (Li et al., 2021). Affected employees may feel insecure and perceive identity threats, which could lead to resistance to AI adoption if the TMT does not provide a clear understanding of the AI's planned impact (Craig et al., 2019). In light of frequent media reports that AI will eventually replace human workers in jobs ranging from the stock exchange to the factory floor, expectation and change management are crucial (Kelly, 2020). As a result, TMTs are urged to develop their firm's *strategic AI orientation* to manage this value identification and strategy stage (Li et al., 2021). AI orientation refers to a "*firm's overall strategic direction and goals associated with introducing and applying AI technology*" (Li et al., 2021) and thus guides AI-related strategic decisions, including AI-related investments and management practices (Ding et al., 2014; Li et al., 2010). By clearly identifying the value of AI for a firm and defining shared objectives, AI orientation helps TMTs decide on investments and communicate the logic of a firm's AI usage to different stakeholders (Li et al., 2021).

Second, once TMTs have successfully established AI orientation, they need to manage the realization of the identified value potentials through the formulated strategy. When moving from the strategy stage to the implementation stage, firms must ensure they possess a range of resources, such as IT, intangible, and human resources (Weber et al., 2022). Among the resources required to successfully implement AI, human resources have been identified as critical (Roepke et al., 2000; Weber et al., 2022). Gaining new talent necessary for AI implementation will require firms to establish policies governing HR-related processes (Rana & Sharma, 2019). Such new policies demand executive attention due to the significant risks associated with the structural adjustments necessary to build and maintain AI-specific human resources (Rana & Sharma, 2019). Consequently, executives should develop their firm's HR-related AI implementation ability to manage the HR-specific aspect of the AI implementation stage (Mikalef et al., 2019). HR-related AI implementation ability is defined as a *firm's HR-related ability to implement IT systems with an AI component* (Weber et al., 2022). For example, quickly attracting and assembling an AI development team or knowing which AI-related positions to recruit and which AI skills to require are part of a firm's HR-related AI implementation ability. To guarantee that the firms have access to the appropriate human talent, they might use internal and external modes of employment (Lepak & Snell, 1999). Internal employment modes include "developing" and "acquiring" human resources, whereas external employment modes comprise "alliancing" and "contracting" human resources (Lepak & Snell, 1999). Each mode has advantages and disadvantages that depend on the use case and context. AI is a continuously evolving topic that necessitates high-value human resources and demands the immediate deployment of relevant skills (Berente et al., 2021). As such, the internal mode of "acquisition" (i.e., employing new personnel) is particularly appropriate and a viable focus when investigating HR-related AI implementation ability (Lepak & Snell, 1999).

## Research model and hypotheses

We developed a research model based on the UET and the ABV to shed light on the relationships between TMT AI literacy, AI orientation, HR-related AI implementation ability, and firm type (Fig. 1). To address RQ1, we hypothesized two effects of TMT AI literacy on AI orientation (H1) and HR-related AI implementation ability (H2) ("Effects of TMT AI literacy" section ). In addition, we investigated the role of AI orientation in this interplay in greater detail ("Mediating effect of AI orientation" section). We examined AI orientation's effect on HR-related AI implementation ability (H3) and its mediating role between TMT AI literacy and HR-related AI implementation ability (H4). To answer RQ2, we tested the moderating role of firm type ("Moderating effects of firm type" section). Therefore, we presumed two moderation effects of firm type on TMT AI literacy's effects on AI orientation (H5a) and HR-related AI implementation ability (H5b). The following subsections expound upon each of the hypotheses presented in Fig. 1.

### Effects of TMT AI literacy on AI orientation and HR-related AI implementation ability

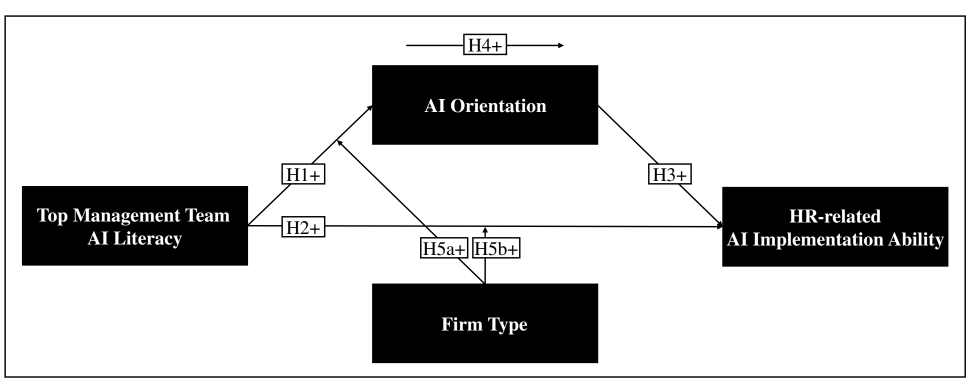
#### Effects of TMT AI literacy

UET and related AI literacy work offer three main reasons suggesting that higher TMT AI literacy positively affects a firm's AI orientation: influence of expertise on the TMT, decision scrutiny of the TMT, and power within the TMT. According to UET, the characteristics of executives who make up the TMT influence strategic decisions. Executives' *expertise* constitutes such an executive's characteristic in the sense of UET, which can influence the TMT's strategic decision-making (Fu et al., 2019). The higher the share of AI-literate executives within the TMT, the more cumulative AI expertise is present within the TMT, helping all TMT members to develop a holistic understanding of AI. Thus, with higher TMT AI literacy, spillover effects of AI literacy between the executives are more likely. Such spillover effects can help less AI-literate executives develop or improve an AI understanding, resulting in more realistic expectations about the possibilities of AI technologies like machine learning. By promoting a thorough understanding of AI and communicating its potential impact, AI-literate executives can motivate other executives to support AI orientation (Li et al., 2021).

*Decision scrutiny* is critical for all TMT decisions due to their significant impact on the firm, its employees, and its business outcomes. Different AI-literate executives within the TMT combine different perspectives of AI. AI literacy comprises not only technological components but also many others, such as AI risk assessment (Long & Magerko, 2020; Mikalef & Gupta, 2021). All identified AI literacy components are far too many to be mastered by one person. Executives will naturally have AI literacy with a different focus based on their educational background and role, that is, they possess varying characteristics in the sense of UET. For instance, an AI-literate engineering-trained CTO, a business-trained chief marketing officer, and a law-trained chief legal officer are likely to have considered AI from their point of expertise. Research has shown that more diverse groups tend to make better decisions, for example, because they can overcome negative framing effects (Yaniv, 2011). The more AI-literate executives a TMT has, the more it combines different executive characteristics and the more AI-related decisions are scrutinized from different perspectives. Furthermore, it makes the executives more likely to comprehend the possible advantages of establishing AI orientation, enabling them to manage the change, risks, and costs related to AI deployment (Li et al., 2021).

How a strategic direction (e.g., AI orientation) is decided in the TMT also depends on the *power* of its proponents within the TMT. According to the ABV of the firm, attention drives resource allocation within a firm (Ocasio, 1997). When more executives are AI-literate, more attention and power flow toward the topic of AI. Hence, the ABV suggests that more AI-literate executives also cause AI orientation to receive more resources. In other words, more AI-literate

**Fig. 1** Research model



executives within the TMT make it easier to find support for AI orientation. Furthermore, Hambrick (2007) notes in his more recent extension of UET that an executive's power has the potential to amplify the effect of their individual characteristics on strategic decisions. Together, based on the influence of expertise on the TMT, decision scrutiny of the TMT, and power within the TMT, we hypothesize the following:

***H1:*** *High (vs. low) TMT AI literacy increases a firm's AI orientation.*

Management literature highlights the significance of executive attention for structural human resource decisions, which suggests that TMTs are urged to consider HR-related AI implementation ability (Rana & Sharma, 2019). Prior research identifies that executives with (non-AI) IT skills are more likely to engage with IT departments (Bassellier et al., 2015), driving executive attention and resources to their issues, according to the mechanism proposed by UET (Hambrick & Mason, 1984). Therefore, higher TMT AI literacy could conceivably have a positive effect on HR-related AI implementation ability. Due to AI's quick-paced nature and the high-value human resources it necessitates, internal employment through the acquisition of talent (i.e., recruiting new people) is one reasonable way to adapt the workforce to AI (Berente et al., 2021; Lepak & Snell, 1999).

Prior research emphasizes that when moving from the strategy phase (i.e., AI orientation) to the implementation stage, HR-related AI implementation ability is one critical factor (Roepke et al., 2000; Weber et al., 2022). Since strategic human resource decisions need executive attention, they are – like AI orientation – discussed within the TMT. Therefore, the reasoning of power within the TMT suggesting higher AI orientation due to higher TMT AI literacy also applies to HR-related AI implementation ability. Thus, a greater share of AI-literate executives within the TMT might increase the power of the proponents behind the position to build HR-related AI implementation ability (i.e., hiring AI talent). As such, we hypothesize the following:

***H2:*** *High (vs. low) TMT AI literacy increases a firm's HR-related AI implementation ability.*

### Mediating effect of AI orientation

While H2 suggests that TMT AI literacy positively affects a firm's HR-related AI implementation ability, other factors might also influence this ability. Formulating a strategic direction, such as AI orientation, is not an end in itself for a firm (Li et al., 2010). For example, research shows that when executives develop strategic direction, firms tend to achieve better financial performance (Sobol & Klein, 2009). Furthermore, a strategic direction communicates the firm's course to internal stakeholders (e.g., middle management or operational employees) and external stakeholders (e.g., job applicants or stock market analysts) (Mohiuddin Babu, 2017). Internally, AI orientation affects how employees perceive and exercise their jobs. Hence, AI orientation might affect how much a human resource department, respectively, the human resource managers or employees, integrate AI-related information into their day-to-day hiring practices (e.g., recruiting activity). Integrating AI-related information in hiring practices increases a firm's ability to hire AI talent. Externally, AI orientation also affects how the public perceives a firm (Jalili et al., 2022). If job seekers with AI literacy perceive a firm as a professional fit, they might be more likely to consider it a potential employer. Increased AI talent supply also increases a firm's ability to internalize AI talent, i.e., its HR-related AI implementation ability.

While TMT AI literacy's effect on HR-related AI implementation ability potentially materializes through the top-down definition of hiring policies, AI orientation's effect potentially materializes via the day-to-day actions of middle management or operational employees and how potential job seekers perceive the firm. Thus, we formulate the following hypothesis:

***H3:*** *High (vs. low) AI orientation increases a firm's HR-related AI implementation ability.*

Based on H1 to H3, AI orientation should mediate TMT AI literacy's effect on HR-related AI implementation ability. H3 suggests conceptually distinct effects of TMT AI literacy (e.g., policy setting) and AI orientation (e.g., day-to-day actions of human resource managers) on HR-related AI implementation ability. Therefore, we presume that AI orientation partially mediates TMT AI literacy's effect on HR-related AI implementation ability, meaning that TMT AI literacy's mediated effect and direct effect on a firm's HR-related AI implementation ability are significant (Zhao et al., 2010). We propose the following mediation hypothesis:

***H4:*** *AI orientation partially mediates the effect of TMT AI literacy on a firm's HR-related AI implementation ability.*

## Moderating effects of firm type

While we presume that TMT AI literacy affects AI orientation (H1) and HR-related AI implementation ability (H2), executives do not act in a vacuum. They operate within the environment of their firm and its customers, partners, and competitors. This environment might affect how effectively executives and TMTs can influence their firms, as noted by Hambrick (2007) in their extension of the basic mechanism of UET. The firm type characterizes typical configurations of different organizational resources in this environment. A segmentation of organizational resource configurations with the potential to affect AI adoption is the distinction between *startup firms* and *incumbent firms* (Kohler, 2016). Both types have different resources that might help TMTs utilize their AI literacy to establish AI orientation and HR-related AI implementation ability.

Startup firms are more flexible and faster than incumbent firms (Leppänen et al., 2023). Startups regularly operate in a fast-paced environment that requires quick adaption to avoid being outcompeted (Pigola et al., 2022). Therefore, they are widely recognized for being agile, adaptable, and innovative, leading to more rapid innovation processes (Benlian, 2022; Criscuolo et al., 2012). According to previous research, the differences between the innovation processes of startup and incumbent firms can be attributed to various factors, such as the ability to explore multiple business models in the absence of an established customer base and legitimacy (Andries et al., 2013). Concerning AI orientation, startups' TMTs could benefit from not being constrained by an existing customer base to formulate their AI strategy due to less risk involved in pivoting their strategy (Andries et al., 2013). Regarding HR-related AI implementation ability, a startup's agile and innovative culture might enhance the TMT's influence because their decisions spread quickly through the company to attract AI talent (Weber et al., 2022).

Incumbent firms also possess organizational resources valuable to AI orientation and HR-related AI implementation ability. Financial resources, which tend to be more substantiated at incumbents, could help their TMTs present a compelling and well-funded AI strategy to the owners, thus improving the firm's AI orientation (Baker & Nelson, 2005). Concerning HR-related AI implementation ability, existing relationships with recruiting companies and an established employer brand might enable incumbents' TMTs to attract AI talent more easily (Weber et al., 2022). On the other hand, the firm type can also restrict the effectiveness of the TMT's influence to a certain degree (Li et al., 2021). In some firms, executives must report to a supervisory board of non-executive directors overseeing them. Such a supervisory board can limit the range of possible actions available to the executives or lead them in a pre-defined direction. In other words, different organizational resources can potentially mitigate or amplify the basic mechanism proposed by UET, i.e., the effect of executives' characteristics on firm characteristics.

Based on the advantages and disadvantages of startups and incumbents discussed above, we hypothesize that startup firms offer a configuration of organizational resources that allows TMTs to have a stronger impact on AI orientation and HR-related implementation ability because their advantages, such as adaptation ability, outweigh the advantages of incumbents, such as stronger financial resources and established relationships. Thus, the organizational resources of startups amplify the UET-based mechanism. Taken together, a startup firm might conceivably enable TMTs to use their AI literacy more effectively, leading to higher AI orientation and HR-related AI implementation ability. Hence, we formulate two moderation hypotheses that relate to the effects stated in H1 and H2:

> ***H5a:*** *Firm type amplifies the effect of TMT AI literacy on AI orientation, such that TMT AI literacy has a stronger effect when the firm type is "startup" (vs. "incumbent").*

> ***H5b:*** *Firm type amplifies the effect of TMT AI literacy on HR-related AI implementation ability, such that TMT AI literacy has a stronger effect when the firm type is "startup" (vs. "incumbent").*

## Methodology

The following section provides detailed information on the methodology employed in our study. We used web scraping to obtain executives' observational literacy data and firm data. Web scraping refers to an approach for retrieving information in a structured manner from a website via a programmed script. This was followed by a text-mining analysis to operationalize the principal variables of our study and regression analysis to answer our research questions. The following explains how we retrieved the executive and firm data ("Data retrieval and preprocessing" secion). After that, we describe the principal and control variables of the study and detail how we operationalized their measurement ("Measurements" section). To ensure the validity of our analysis, we conducted several robustness checks, which are available in Appendix B (AI distinctiveness of principal variables, alternative operationalization of principal variables, sample selection bias, analyses segmented by firm type, and reverse causality of AI orientation).

### Data retrieval and preprocessing

The first step in our data retrieval process was to select a suitable sample of firms for our research questions. We aimed to include a broad mix of industries to ensure our findings are generalizable. Since we explicitly sought to uncover the differences between incumbent and startup firms with RQ2, we aimed to include a representative subsample of both groups in our overall sample. Therefore, we leveraged two sources: We used the standard stock index S&P500 to select our subsample of incumbent firms (list retrieved in July 2022). To choose our subsample of startup firms, we used an up-to-date list of so-called "unicorns" (privately held firms with a valuation above 1 billion USD, which are not older than ten years) also retrieved in July 2022 from CB Insights (2022).

### Executive data

After selecting the sample, we gathered the necessary executive and firm data. While research has analyzed user-disclosed data of executives in social networks (Heavey et al., 2020), IS skill studies have focused on requested skills (i.e., job postings) as opposed to existing skills (i.e., skills in online profiles) (Anton et al., 2020; Debortoli et al., 2014; Gardiner et al., 2017). To collect data on TMT AI literacy, we retrieved observational literacy data of the firm's executives from LinkedIn.com, the largest global professional social network (> 850 million users in April 2023 (LinkedIn.com, 2023)). In this professional social network, individuals can create online profiles with a dedicated section describing their competencies, knowledge, and skills. They then populate their online profiles with their data and link them to their current and past employers. We compiled a list of all executives from the included firms in the sample based on information the firms disclosed about their TMTs on their websites. Then, we extracted the relevant disclosed literacy data of each executive's online profile in textual form with a web scraping procedure. Since we extracted the literacy data from a dedicated section of the online profiles, they were already separated from the nonrelevant text, which made removing stop words unnecessary. Furthermore, this enabled us to include competencies, knowledge, and skills that consist of multiple words, such as "machine learning." Separately, these words would have a different meaning than combined. We recorded the entries exactly as the executives entered them into their profiles. As the text mining literature recommends, the extracted text data was then lemmatized to unify the data set (Anton et al., 2020; Kortum et al., 2022; Sidorova et al., 2008). We replaced acronyms, such as "ML" for machine learning, with their full terms to unify the entry labeling. Additionally, we obtained profile information, such as the executives' official role descriptions. We included only firms that publicly disclosed their executives and where we were able to retrieve the literacy data from at least three executives to include only TMTs, of which we likely have recorded a majority (average TMT size = 6 (Simons et al., 1999)). In total, we retrieved 344,411 individually disclosed literacy components from 6,986 executives between July and September 2022. The executives belonged to 645 different firms, thereof 477 incumbent firms and 168 startup firms.

### Firm data

We used information disclosed by the firms on LinkedIn.com and official annual reports (10-K statement) to collect the additional necessary firm data. On LinkedIn.com, firms can publish job postings and share firm-related information as posts (robustness check for sample selection bias see Appendix B.3). To compile data on a firm's HR-related AI implementation ability, we retrieved the requested skill data in all current job postings of firms in the sample with the same web scraping procedure as used above. In sum, we retrieved 10,774,669 individually demanded skills from 207,232 job postings between July and September 2022. The skill data was processed as described for the executives.

Regarding the firm's AI orientation, we retrieved the incumbent firms' latest 10-K statement (available at the official US government website: "www.sec.gov"), which includes a dedicated discussion of the TMT regarding the firm's current situation and future intentions ("Management Discussion and Analysis" (MD&A)) (Bochkay & Levine, 2017). The publication of the latest available 10-K statement ranged from December 2021 to October 2022, depending on the business year of the respective firm. Since startup firms are not obliged to disclose official reports, such as 10-K statements, we retrieved all available posts of the firms from the same period and on the same professional social network (LinkedIn). Such firm posts have a similar function to the MD&A in a 10-K statement, which is communicating the firm's situation and future intentions to external stakeholders. In the following section, we provide detailed information on how we used the retrieved data to operationalize the variables of this study.

## Measurements

### TMT AI literacy

To measure the TMT AI literacy of a firm, we first determined which individual executives in our sample are "AI-literate." Following prior research (Alekseeva et al., 2021), we used a detailed taxonomy of AI skills and competencies (Appendix A) and tested whether an executive possessed skills and competencies from the taxonomy. We view an executive as AI-literate if they possess at least one entry (out of 71) from the taxonomy. A firm's TMT AI literacy is then measured with the *share of AI-literate executives on the firm's TMT*. As such, the measure ranges between 0 and 1.

### AI orientation

We followed prior research in operationalizing our measurement of AI orientation (Li et al., 2021). AI orientation refers to a *firm's overall strategic direction and goals associated with introducing and applying AI technology*. To measure such an association with AI, we leveraged the AI skill and competencies taxonomy (Appendix A) as a detailed set of AI-related keywords and analyzed their occurrence in the firm's communication. Research has shown that the MD&A from a firm's 10-K statement reflects its strategy and is a valuable predictor of such firm characteristics (Bochkay & Levine, 2017). Hence, we leverage the MD&A of incumbent firms to measure their AI orientation. As private firms are not obliged to disclose an MD&A, we used the firm's communication via their posts on the professional social network to measure the AI orientation of startup firms (Mattke et al., 2019). Subsequently, we determined the relative frequency of all AI-related keywords within all words of each firm's communication. To make the AI orientation measurement of incumbent and startup firms comparable due to different average document lengths, we standardized the relative frequency of AI-related keywords by each firm type (incumbent and startup) based on the firm with the highest frequency within each type. As a result, we get a score ranging between 0 and 1, where "1" refers to the firm(s) with the highest AI orientation and "0" to the firm(s) with no AI orientation.

#### Alternative operationalization of AI orientation (for robustness checks)

We argue that a greater occurrence of AI-related keywords indicates that a firm has thoroughly considered AI and developed a more well-founded AI orientation. However, the applicability of AI is highly context-dependent, and some firms might have made a strategic decision not to engage in AI or only minimally engage in it. To provide a more robust analysis, we construct an alternative binary operationalization of AI orientation, which measures not the frequency of AI-related keywords but only if at least one AI keyword occurred in the firm's communication ("AI orientation binary"). Even if a firm strategically decides not to or minimally engage in AI in its AI orientation development process, a binary measurement can measure such a discussion since AI-related keywords will occur (but with a lower frequency) (Li et al., 2021).

#### HR-related AI implementation ability (HAIIA)

To measure a *firm's HR-related ability to implement IT systems with an AI component*, we consider the AI skills it demands in its workforce via hiring. Therefore, we leverage the obtained job postings of all firms in our sample and determine the presence of AI skills within the demanded skills in each posting based on the introduced AI skill and competence taxonomy (Appendix A). To compute the HR-related AI implementation ability measure, we determine if AI skills are demanded in a job posting. Then, we measure HR-related AI implementation ability with the share of a firm's job postings requiring AI skills of all job postings from the firm. Therefore, the measurement ranges between 0 and 1.

Several reasons support the measure's appropriateness for the context of our study. First, prior IS research investigated job postings and asserted they give "insights into trends into employment and workforce skills" (Gardiner et al., 2017, p. 2) and are the "prevalent method in IS literature to […] reflect the current status in the labour market" (Anton et al., 2020, p. 5). Furthermore, economic research finds that firms' skill demand for professional workers (i.e., workers with complex skills like AI) is associated with firm performance and employee wages, indicating that demanded skills send valid signals about a firm's human resources that can contribute to value generation (Deming & Kahn, 2018). Romanko and O'Mahony (2022) underscore this assertion generally but also point out that one needs to acknowledge that the measure is limited by the assumption that demanded skills translate into existing skills at the firm. Second, we argue that in our context, which focuses on HR-related AI implementation ability, such an organizational ability entails human resources able to implement AI but also—before that—the ability to judge which AI skills are needed as well as the ability to internalize these (Coombs et al., 2020). Therefore, generating the appropriate demand for AI skills is in itself also an expression of HR-related AI implementation ability. Given the rapid evolution of AI technologies and the corresponding skill requirements (Cetindamar et al., 2022), the ability to swiftly create and change AI skill demand is paramount (Kruse et al., 2019). In summary, we believe the measure, which adheres to IS standards, is appropriate for our context despite its inherent limitation: first, one can reasonably assume an association between a firm's demanded skills and its available human resources contributing to the ability to implement (future) AI, and second, HR-related AI implementation ability also consists in the ability to internalize human resources which is reflected in the process of creating relevant AI-related job postings.

#### Alternative operationalization of HR-related AI implementation ability (for robustness checks)

Similar to AI orientation, we argue for HR-related AI implementation ability that the more AI skills a firm possesses, the better it will be able to implement IT systems with an AI component. However, one might argue that different business models necessitate different optimal levels of AI skills in a firm's workforce, which means that more is not always better. Therefore, we construct two alternative operationalizations. First, we construct a binary measurement indicating whether a firm demands AI skills at all ("HAIIA-binary"). Hence, the alternative binary operationalization accounts for different business models. Second, we construct an indicator measuring the presence of AI skills and the breadth of AI skills. Therefore, we compute for each job posting not only if the firm demands AI skills but also how many different AI skills it demands. We describe each job posting with an "AI skills breadth," defined as the unique demanded AI skills in the posting divided by the number of all AI skills searched for (see Appendix A). Then, we construct the firm's overall AI skill breadth ("HAIIA-breadth") as the sum of all job postings' AI skill breadths divided by the number of job postings. Hence, the HAIIA-breadth ranges between 0 and 1.

#### Control variables

We implemented control variables on the *TMT*, *firm*, and *industry* levels to ensure the validity of our analysis. On the *TMT level*, prior research identified an effect of CIO presence within the TMT on AI orientation (Li et al., 2021). Furthermore, studies assert that CIO and CTO roles sometimes overlap (Haffke et al., 2016; Peppard et al., 2011). Hence, our analysis includes *CIO* and *CTO presence* as binary control variables. Two independent raters assessed the TMTs of the firms in the data set and coded in a binary manner whether a CIO or CTO was present in the firm based on the role title of the executives. Interrater agreement was satisfactory ($K = 0.93$, Cohen (2016)), and raters discussed discrepancies to achieve full agreement. Additionally, we included the number of executives as a control variable to account for *TMT-size* effects, such as the agility of smaller TMTs (Li et al., 2021).

On the *firm level*, we included control variables used in the quantitative analysis of firms, such as *firm age* (in years) and *firm size* (in the number of employees) (Rothaermel & Deeds, 2004). Since we consider job postings in our analytical approach, we include the number of job postings as a control variable. Furthermore, one might argue that AI orientation and HR-related AI implementation ability are not distinct from general IT orientation or general HR-related IT implementation ability. Hence, we measure IT orientation and HR-related IT implementation ability with procedures similar to those described above for their AI-specific counterparts. On the one hand, this enables us to control the influence of general *IT orientation* on AI orientation and HR-related AI implementation ability. On the other hand, we can replace the AI-specific dependent variables in our research model with their general IT counterparts to assess if AI orientation and HR-related AI implementation ability are distinct, thus increasing the robustness of our analysis. We follow prior IS research in selecting the key terms to measure the two IT-related variables (Li et al., 2021). The selected key terms are ERP (enterprise resource planning), CRM (client relationship management), SCM (supply chain management), CAM (computer-aided manufacturing), and MIS (management information systems).

On the *industry level*, we included the firms' primary *industry classification* as a control variable. AI might be more relevant in specific industries, for example, because there are more potential AI use cases in the business context. We used the first level of the North American Industry Classification System (NAICS). Each industry is operationalized with a binary control variable. A list of all included industries is available in Table 2.

For further *robustness*, we conducted analyses segmented by firm type (startup vs. incumbent), allowing us to include financial control variables when analyzing only incumbent firms available from their 10-K statements. We included *net income* (in USD) to account for financial performance effects (Bos et al., 2017); *cost of goods sold* (in USD) and *overhead costs* (in USD) to account for potential innovation investment effects (Baumers et al., 2016); *leverage*, measured as the ratio of long-term debt to the total asset (in %) since firms with higher leverage have potentially more capital to allocate for innovation (Swift, 2016); and *ownership concentration* as the share of the largest shareholder (in %) to account for effects of ownership structure on innovation (Zhang et al., 2018).

## Results

We use an OLS regression model with the statistical software "R" (version 4.2.0) to analyze our data. For the mediation analysis, we used the R-package "mediation" (version 4.5.0). In the following chapter, we report our results expressed in the order of the presented hypothesis ("Effects of TMT AI literacy" section, "Mediating effect of AI orientation" section, and "Moderating effect of firm type" section). Descriptive statistics and correlations are available in Table 3. A summary of the main results is available in Fig. 2. The results of the conducted robustness checks are available in Appendix B.

### Effects of TMT AI literacy on AI orientation and HR-related AI implementation ability

#### Effects of TMT AI literacy

Our first hypothesis (H1) stated that a high (vs. low) TMT AI literacy increases a firm's AI orientation. We tested H1 with model 1 in Table 2 and found that TMT AI literacy positively affects AI orientation ($\beta = 0.409$, $p < .001$). Thus, we conclude support for H1.

The second hypothesis (H2) stated that a high (vs. low) TMT AI literacy increases a firm's HR-related AI implementation ability. We tested H2 with model 2 in Table 2. In model 2, we also control for a potential influence of AI orientation on HR-related AI implementation ability. TMT AI literacy positively affects HR-related AI implementation ability ($\beta = 0.795$, $p < .001$). Thus, we conclude support for H2.

**Table 2** Regression results

| DV (model ID) variable | AIO[1] (1) | | HAIIA[2] (2) | | HAIIA (3) | | AIO (4) | | AIO (5) | | HAIIA (6) | | HAIIA (7) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | β | s.e. | β | s.e. | β | s.e. | β | s.e. | β | s.e. | β | s.e. | β | s.e. |
| Constant | (0.021) | 0.042 | 0.009 | 0.073 | 0.057 | 0.083 | (0.017) | 0.042 | (0.015) | 0.042 | 0.006 | 0.073 | 0.002 | 0.073 |
| TMT AI literacy (TMTAIL) | **0.409*** ** | **0.029** | **0.795*** ** | **0.059** | | | **0.426*** ** | **0.032** | **0.559*** ** | **0.077** | **0.783*** ** | **0.064** | **0.439** ** | **0.140** |
| *Mediator* | | | | | | | | | | | | | | |
| AI orientation (AIO) | | | **0.648*** ** | **0.070** | **1.107*** ** | **0.070** | | | | | **0.649*** ** | **0.070** | **0.664*** ** | **0.070** |
| *Moderator* | | | | | | | | | | | | | | |
| Firm type (FT) | | | | | | | **(0.018)** | **0.015** | **(0.005)** | **0.016** | **0.012** | **0.026** | **(0.020)** | **0.029** |
| TMTAIL × FT | | | | | | | | | **(0.161)** | **0.084** | | | **0.409** ** | **0.148** |
| *Controls* | | | | | | | | | | | | | | |
| CIO presence | (0.016) | 0.010 | (0.015) | 0.017 | (0.017) | 0.019 | (0.018) | 0.010 | (0.018) | 0.010 | (0.014) | 0.017 | (0.013) | 0.017 |
| CTO presence | (0.010) | 0.009 | (0.024) | 0.015 | 0.005 | 0.017 | (0.009) | 0.009 | (0.011) | 0.009 | (0.025) | 0.016 | (0.019) | 0.016 |
| TMT size | 0.001 | 0.001 | 0.001 | 0.002 | < 0.001 | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 |
| Firm age | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001* | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 |
| Firm size | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 |
| Number of job postings | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001* | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 | < 0.001 |
| IT orientation | (0.060) | 0.047 | 0.028 | 0.082 | 0.079 | 0.093 | (0.062) | 0.047 | (0.068) | 0.047 | 0.030 | 0.082 | 0.048 | 0.082 |
| *Industry controls* | | | | | | | | | | | | | | |
| Agriculture[3] | (0.003) | 0.064 | < 0.001 | 0.113 | 0.006 | 0.128 | (0.006) | 0.064 | (0.012) | 0.064 | 0.002 | 0.113 | 0.017 | 0.112 |
| Construction | 0.005 | 0.057 | (0.016) | 0.101 | (0.006) | 0.114 | 0.004 | 0.057 | < 0.001 | 0.057 | (0.016) | 0.101 | (0.005) | 0.100 |
| Finance and insurance | (0.006) | 0.042 | (0.011) | 0.074 | 0.027 | 0.084 | (0.002) | 0.043 | (0.007) | 0.043 | (0.013) | 0.075 | (0.002) | 0.074 |
| Health care[4] | (0.008) | 0.045 | 0.018 | 0.079 | 0.062 | 0.090 | 0.001 | 0.046 | (0.007) | 0.046 | 0.012 | 0.080 | 0.030 | 0.080 |
| Information | (0.001) | 0.056 | (0.013) | 0.097 | (0.015) | 0.111 | (0.003) | 0.056 | (0.005) | 0.056 | (0.011) | 0.098 | (0.006) | 0.097 |
| Manufacturing | 0.017 | 0.041 | 0.026 | 0.073 | 0.050 | 0.082 | 0.017 | 0.041 | 0.012 | 0.041 | 0.026 | 0.073 | 0.037 | 0.072 |
| Mining[5] | 0.014 | 0.046 | (0.009) | 0.081 | 0.005 | 0.092 | 0.014 | 0.046 | 0.010 | 0.046 | (0.009) | 0.081 | 0.001 | 0.081 |
| PST services[6] | 0.008 | 0.042 | 0.028 | 0.074 | 0.107 | 0.083 | 0.013 | 0.042 | 0.007 | 0.042 | 0.024 | 0.074 | 0.039 | 0.074 |
| Real estate[7] | 0.013 | 0.045 | (0.004) | 0.079 | (0.019) | 0.090 | 0.011 | 0.045 | 0.009 | 0.045 | (0.002) | 0.079 | 0.002 | 0.079 |
| Retail trade | < 0.001 | 0.046 | (0.015) | 0.080 | 0.014 | 0.090 | 0.003 | 0.046 | 0.002 | 0.046 | (0.017) | 0.080 | (0.013) | 0.079 |
| Transportation[8] | (0.022) | 0.045 | 0.106 | 0.078 | 0.167 | 0.088 | (0.016) | 0.045 | (0.022) | 0.045 | 0.101 | 0.079 | 0.117 | 0.078 |
| Utilities | 0.013 | 0.050 | 0.026 | 0.088 | 0.006 | 0.099 | 0.011 | 0.050 | 0.010 | 0.050 | 0.028 | 0.088 | 0.030 | 0.087 |
| Wholesale trade | 0.056 | 0.050 | (0.019) | 0.087 | (0.033) | 0.099 | 0.056 | 0.050 | 0.055 | 0.050 | (0.020) | 0.088 | (0.018) | 0.087 |

**Table 2** (continued)

| DV (model ID) variable | AIO[1] (1) | | HAIIA[2] (2) | | HAIIA (3) | | AIO (4) | | AIO (5) | | HAIIA (6) | | HAIIA (7) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | s.e. | $\beta$ | s.e. | $\beta$ | s.e. | $\beta$ | s.e. | $\beta$ | s.e. | $\beta$ | s.e. | $\beta$ | s.e. |
| $R^2$ | 0.279 | | 0.521 | | 0.381 | | 0.281 | | 0.285 | | 0.521 | | 0.527 | |
| Adjusted $R^2$ | 0.255 | | 0.504 | | 0.360 | | 0.256 | | 0.259 | | 0.503 | | 0.508 | |
| $P$-value of $f$-statistic | < .001 | | < .001 | | < .001 | | < .001 | | < .001 | | < .001 | | < .001 | |
| $n$ | 645 | | 645 | | 645 | | 645 | | 645 | | 645 | | 645 | |

Significance levels: * = $p < .05$, ** = $p < .01$, *** = $p < .001$

[1]AI orientation

[2]HR-related AI implementation ability

[3]Agriculture, forestry, fishing, and hunting

[4]Health care and social assistance

[5]Mining, quarrying, and oil and gas extraction

[6]Professional, scientific, and technical services

[7]Real estate and rental and leasing

[8]Transportation and warehousing

**Table 3** Descriptive statistics and correlations ($n = 645$)

| Variable | Unit | Mean | SD | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Top management team AI literacy (1) | % | 0.084 | 0.152 | 1 | | | | | | | | | | |
| AI orientation (2) | % | 0.031 | 0.115 | 0.503*** | 1 | | | | | | | | | |
| HR-related AI implementation ability (3) | % | 0.108 | 0.247 | 0.662*** | 0.555*** | 1 | | | | | | | | |
| Firm type (4) | Binary (0 = incumbent, 1 = startup) | 0.260 | 0.439 | 0.574*** | 0.208*** | 0.389*** | 1 | | | | | | | |
| CIO presence (5) | % | 0.282 | 0.450 | (0.175)*** | (0.113)** | (0.157)*** | (0.309)*** | 1 | | | | | | |
| CTO presence (6) | % | 0.389 | 0.488 | 0.243*** | 0.082* | 0.122** | 0.316*** | (0.147)*** | 1 | | | | | |
| TMT size (7) | # of executives | 10.7 | 4.7 | (0.062) | (0.002) | (0.023) | (0.123)** | 0.281*** | 0.154*** | 1 | | | | |
| Firm age (8) | Years | 56.2 | 60.4 | (0.312)*** | (0.128)** | (0.232)*** | (0.483)*** | 0.243*** | (0.178)*** | 0.135*** | 1 | | | |
| Firm size (9) | # of employees | 42,717 | 130,473 | (0.066) | 0.014 | (0.055) | (0.190)*** | 0.040 | (0.007) | 0.088* | 0.094* | 1 | | |
| Number of job postings (10) | # of job postings | 307 | 350 | (0.220)*** | (0.026) | (0.156)*** | (0.426)*** | 0.176*** | (0.107)** | 0.092* | 0.253*** | 0.355*** | 1 | |
| IT orientation (11) | % | 0.019 | 0.084 | 0.039 | (0.020) | 0.026 | 0.006 | (0.037) | 0.033 | (0.001) | 0.020 | (0.014) | (0.003) | 1 |

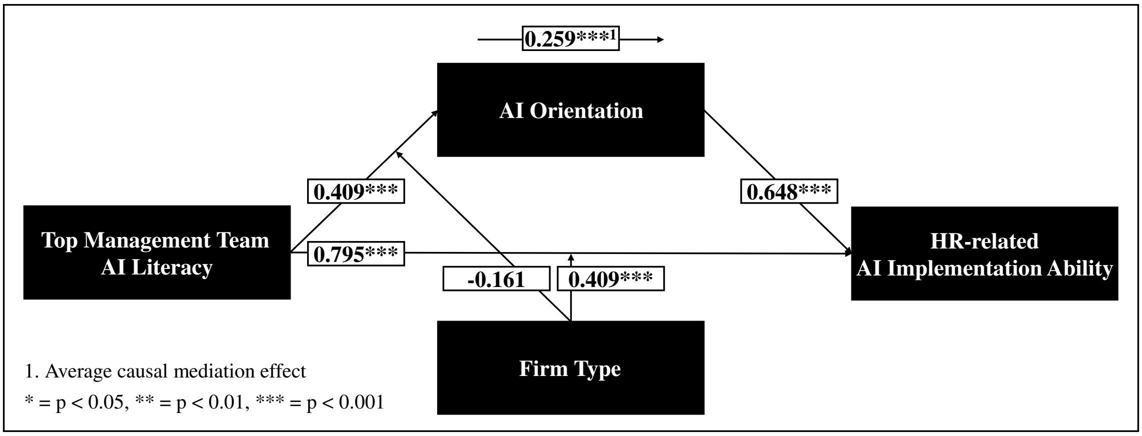



**Fig. 2** Research model with results

### Mediating effect of AI orientation

Before testing the mediation of AI orientation, we assess the effect of AI orientation on HR-related AI implementation ability. H3 presumed that a high (vs. low) AI orientation increases a firm's HR-related AI implementation ability. We tested H3 with models 2 and 3 in Table 2. In model 3, AI orientation positively affects HR-related AI implementation ability ($\beta = 1.107$, $p < .001$). In model 2, we find that AI orientation's effect on HR-related AI implementation ability is still significant when TMT AI literacy's effect on HR-related AI implementation ability is accounted for ($\beta = 0.648$, $p < .001$). Therefore, we can conclude support for H3.

Our mediation hypothesis (H4) stated that AI orientation partially mediates the effect of TMT AI literacy on a firm's HR-related AI implementation ability. We tested H4 using bootstrapping to construct confidence intervals of the mediation and direct effect. The strength of bootstrapping is that it does not assume a normal distribution, leading to high statistical power. Bootstrapping involves the test of three paths: path $a$ from the independent variable (TMT AI literacy) to the mediator (AI orientation), path $b$ from the mediator to the dependent variable (HR-related AI implementation ability), and path $c$ from the independent variable to the dependent variable. Thus, path $a \times b$ represents the "average causal mediation effect" while path $c$ represents the "average direct effect." The collected data were resampled 5000 times as part of the bootstrapping process, following previous IS research (Rana et al., 2021). The coefficients of paths $a$ and $b$ were multiplied in each resample. The product represents the estimated mediated effect on the dependent variable. We compute confidence intervals based on these resampled values. If zero is not included in the confidence interval, the path is significant at a 95% confidence level. Full mediation is supported when only the average causal mediation effect is significant. The mediation is partial when the average causal mediation effect and the direct effect are both significant. Table 4 summarizes the results of our mediation analysis. Both paths ($a \times b$ [$\beta = 0.259$] and $c$ [$\beta = 0.816$]) are significant. The proportion of the total effect on HR-related AI implementation ability mediated by AI orientation is 0.241. Hence, we conclude support for H4.

### Moderating effect of firm type

Hypotheses H5a and H5b propose moderation effects of firm type on the effects of TMT AI literacy on AI orientation (H5a) and HR-related AI implementation ability (H5b). Both hypotheses state that firm type amplifies the effect of TMT AI literacy on the respective dependent variable, such that TMT AI literacy has a stronger effect when the firm type is startup (vs. incumbent). First, we assess if firm type directly

**Table 4** AI orientation's mediation effect of TMT AI literacy's effect on AI implementation ability

| Effects | Estimate ($\beta$) | 95% confidence interval | | Zero included |
|---|---|---|---|---|
| | | Lower bound | Upper bound | |
| Average causal mediation effect (ACME) (= path $a \times b$) | **0.259*** | 0.166 | 0.370 | No |
| Average direct effect (ADE) (= path $c$) | **0.816*** | 0.651 | 0.970 | No |
| Total effect (TE) (= ACME + ADE) | **1.075*** | 0.936 | 1.220 | No |
| Proportion mediated (= AMCE/TE) | **0.241*** | 0.155 | 0.350 | No |

* = $p < .05$

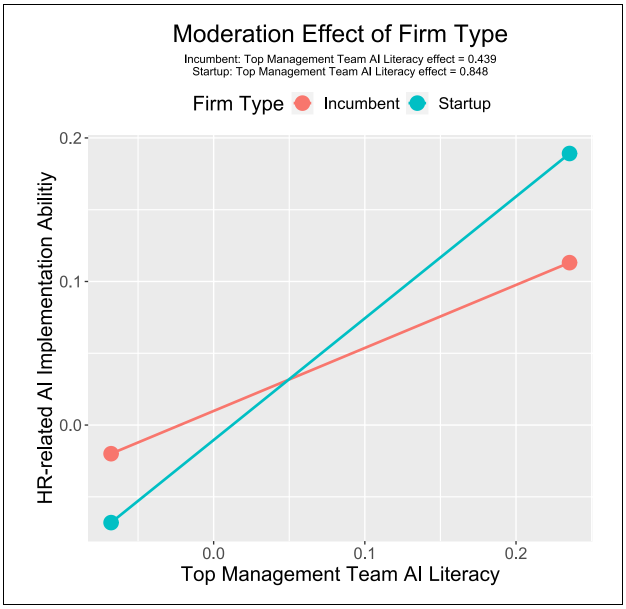



**Fig. 3** Moderation effect of firm type on the relationship between TMT AI literacy and HR-related AI implementation ability

affects AI orientation (Table 2, model 4) or HR-related AI implementation ability (Table 2, model 6). Therefore, the firm type is coded binary (0 = incumbent firm, 1 = startup firm). We find that firm type has neither a significant direct effect on AI orientation ($\beta = -0.018$, $p > .05$) nor HR-related AI implementation ability ($\beta = -0.012$, $p > .05$). To test the moderation, we compute the interaction terms for TMT AI literacy and firm type. In model 5, we find no support for the hypothesis that firm type moderates TMT AI literacy's effect on AI orientation (TMTAIL × FT: $\beta = -0.161$, $p > .05$). Thus, we reject H5a. However, we do find support in model 6 for the hypothesis that firm type moderates TMT AI literacy's effect on HR-related AI implementation ability (TMTAIL × FT: $\beta = 0.409$, $p < .01$). Furthermore, the coefficient of the interaction term is positive, which means that the moderation appears in the hypothesized direction (i.e., the firm type "startup" amplifies the effect). Figure 3 (moderation plot) visualizes how TMT AI literacy's effect on HR-related AI implementation ability is stronger for high levels of TMT AI literacy if the firm type is "startup" compared to the firm type "incumbent." Thus, we find support for H5b.

## Discussion

This study set out to explore how TMTs can more successfully foster the development and adoption of AI within their firms to seize the business value that AI promises due to its recent advancements and avoid potential threats to their long-term competitive position. While research and practitioners consistently see AI as an enabler of business value, many firms fail to generate value with AI (Ransbotham et al., 2019; Reis et al., 2020). With respect to upper echelons, IS research has approached this pertinent issue with a focus on AI strategy-related firm characteristics using a role-oriented view of individual executives (Li et al., 2021) or by emphasizing high-level support of the top management for the topic of AI in general (Pumplun et al., 2019; Reis et al., 2020). Whereas adjunct AI research streams offer AI-related concepts with the potential to improve AI adoption and unlock AI's business value, these have not been applied to executives so far. AI literacy research investigates the human holistic proficiency to use and collaborate effectively with AI, currently focused on users and developers (e.g., Ng et al., 2021; Sambasivan et al., 2021). Organizational capability research explores crucial AI implementation factors, currently focused on conceptualizing these (non-executive) human, intangible, and IT resources (e.g., Mikalef & Gupta, 2021; Weber et al., 2022). Our study draws on these adjunct AI research streams to enhance our understanding of how TMTs affect AI-related firm characteristics, illuminate their often-overlooked role in enabling AI implementation ability, and unveil the contextual impact of firm type.

We introduced TMT AI literacy as a skill-oriented construct and found that it is positively associated with a firm's AI orientation while controlling for the presence of executive roles identified by prior research (Li et al., 2021). This result suggests that AI orientation hinges on the collective TMT AI literacy, not individual executive roles. It underscores the claim of AI's wide-ranging strategic relevance across diverse TMT concerns, from legal liabilities to workforce dynamics and business processes (Shollo et al., 2022). AI orientation seems to be achieved best when AI is addressed holistically from different perspectives. As such, TMT AI literacy underlines the relevance of all executives for formulating strategic AI orientation to promote value-generating AI adoption, which aligns with the ABV, emphasizing the relevance of executive attention overall. Particularly in the light of prior executive IS research, which focuses predominantly on CIOs and CTOs (e.g., Chen et al., 2014; Haffke et al., 2016; Peppard et al., 2011), this result urges to broaden the scope when investigating AI-related topics. Furthermore, prior TMT research emphasizes that TMT diversity concerning gender, age, education, and experience can enhance the positive effects of technology (Kent Baker et al., 2020; Naranjo-Gil, 2009). Our results qualify these findings by indicating that TMT diversity should be combined with TMT AI literacy. While requiring AI literacy for all TMT members reduces skill diversity in principle, AI literacy appears to be an essential executive requirement to drive their attention. Therefore, we argue that TMTs should be diverse regarding domain experience and background but universally AI-literate to balance the executive attention (in the sense of the ABV) appropriately in the age of AI.

Despite recognizing AI value via AI orientation, many firms still struggle to realize the identified value potential (Herper, 2017; Williams, 2021). As such, it is crucial to better understand how to improve AI implementation ability to realize such value. We introduced HR-related AI implementation ability and found that it is positively affected by TMT AI literacy and AI orientation. Through these results, we emphasize the critical role of AI implementation factors, notably human resources (e.g., Mikalef & Gupta, 2021; Pumplun et al., 2019; Weber et al., 2022), and offer guidance on enhancing HR-driven AI implementation. On the one hand, the positive effect of TMT AI literacy on HR-related AI implementation ability indicates that AI-literate TMTs have an impact beyond AI strategy. When TMTs possess AI literacy, their attention on the topic brings not only strategic insights but also the ability to navigate the complexities of AI-driven projects, effectively communicate their vision, and lead their organizations toward successful AI adoption. This qualifies prior research identifying general TMT support as decisive for IT innovation adoption (Rai et al., 2014; Ramamurthy et al., 2008). Furthermore, it aligns with prior research on executive IT literacy, which has demonstrated that executives with higher IT skills tend to exhibit a greater propensity for engaging with IT initiatives (Bassellier et al., 2003; Bassellier et al., 2015). On the other hand, AI orientation's impact on HR-related AI implementation ability shows that AI orientation, which also includes communicating the AI strategy (e.g., via 10-K statements), is not a goal in itself or only for external purposes but that it facilitates HR-related AI implementation ability. Therefore, we support the claim that AI orientation is central to adopting AI because it also promotes implementation beyond defining the target picture (Li et al., 2021). In addition, we showed that TMT AI literacy's effect on HR-related AI implementation ability is partially mediated by AI orientation. This finding shows that TMT AI literacy's effect on HR-related AI implementation ability cannot fully be attributed to TMT AI literacy's effect on AI orientation. Rather, TMT AI literacy seems to affect HR-related AI implementation ability directly and indirectly through AI orientation. As such, this partial mediation also supports the claims made above and potential explanations mentioned in prior literature that executives directly affect implementation ability, for example, through hiring policies (Rana & Sharma, 2019).

Lastly, we found that firm type moderates TMT AI literacy's effect on HR-related AI implementation ability, such that the effect is stronger in startup firms than incumbent firms. In contrast, we did not find any support for a moderation effect of firm type on TMT AI literacy's effect on AI orientation. In the context of firm types representing different organizational resource configurations (Andries et al., 2013; Baker & Nelson, 2005), prior research has shown that these configurations seem to differ in their ability to adopt AI (Oehmichen et al., 2023) and how they support executives to achieve their goals. Our findings qualify this by zooming in on the process of adopting AI and showing that TMTs' impact on AI strategy development is more independent from the firm type (i.e., its resource configuration) than TMTs' impact on AI implementation ability. This suggests that considering how one's firm type can be leveraged or how its disadvantages must be mitigated is more relevant when implementing AI than when developing an AI strategy. The findings imply that a startup's resource configuration, including agility and other factors (Davenport & Bean, 2018; Steiber & Alänge, 2020), may not necessarily give an upper hand in translating TMT AI literacy into effective AI orientation. However, when it comes to HR-related AI implementation ability, a startup's resource configuration seems to make a difference. As such, we underline Hambrick's (2007) extension of UET and answer their call to identify further moderating factors.

## Contributions to research

This study makes three main contributions to upper echelons and AI literacy literature. Our primary contribution is the introduction of a skill-oriented perspective on a firm's TMT and its specification for the AI context in the form of TMT AI literacy. We extend upper echelons research by considering the person beyond the role, and AI literacy research by considering executives beyond developers and users. Prior IS upper echelons research mainly relied on a role-oriented view, which suffers from the fact that executive roles, like CIOs, are often ambiguously defined (Haffke et al., 2016). A skill-oriented perspective constitutes a valuable complement because it allows one to consider the person behind the role who possesses a specific literacy. Moreover, previous AI literacy research has primarily investigated users and developers (e.g., Ng et al., 2021; Sambasivan et al., 2021) but asserted at the same time that AI literacy is stakeholder-specific and called particularly for research on executives (Arrieta et al., 2020; Benlian et al., 2022). Through the introduction of TMT AI literacy, we extend these conversations by placing executives as a relevant stakeholder group on the landscape of the scientific discourse.

Second, we introduce HR-related AI implementation ability in the upper echelons context and bridge the gap between AI value identification (achieved through AI strategy) and AI value realization (achieved through AI implementation). Past research has predominantly focused on either AI strategy (e.g., Li et al., 2021) or AI implementation (e.g., Mikalef & Gupta, 2021; Weber et al., 2022). The relevance of AI strategy development to AI implementation has been underexplored. We shed light on this link from an upper echelons' perspective by specifying how HR-related AI implementation ability is—directly and indirectly—affected by TMT AI literacy and AI orientation. We uncover AI orientation's positive effect on HR-related AI implementation ability and its partially mediating function for TMT AI literacy's effect.

Thirdly, we bring a fresh perspective to upper echelons research by considering differences between startups and incumbents. Building on the notion that TMT effects are firm-context-dependent (Hambrick, 2007), we enhance our understanding of how TMT AI literacy impacts firm characteristics necessary for value-generating AI adoption by factoring in the moderating role of firm type. Previous research focused on collaboration challenges between firm types in AI adoption (Oehmichen et al., 2023). We go further by revealing how a startup context benefits the development of HR-related AI implementation ability. This insight helps us discern the significance of startup resources like agility in AI strategy development compared to implementation (Leppänen et al., 2023). By introducing firm type's moderating influence, we forge a link between AI adoption and management research.

## Practical implications

Regarding practice, our study has implications for the design of executive roles and TMTs, as well as for management approaches. Since higher AI literacy promotes AI orientation and HR-related AI implementation ability, especially in industries where AI likely has a significant value potential, practitioners are urged to consider the whole TMT regarding AI literacy. Each executive role within the TMT might have a specific form of AI literacy tailored to their area of responsibility. Nevertheless, our results suggest that value-generating AI adoption is more likely to be achieved when more TMT members have AI literacy. Allocating "the topic AI" to only one role and requiring only this role to be AI-literate will hinder AI adoption. Instead, shareholders should require all executives to gain AI literacy, adjust role requirements to necessitate AI literacy, and consider AI literacy when hiring executives.

Furthermore, an extended understanding of firm type's moderating effects can offer valuable advice for executives concerning their management approach to AI orientation and implementation. When leading a company with a less adaptable organizational resource configuration for TMT-driven AI adoption (e.g., an incumbent), TMTs can proactively allocate their efforts to eliminate obstacles that might limit the TMT's influence. This could involve strategically prioritizing the development of a data-centric culture during AI implementation (Toutaoui et al., 2022). Moreover, executives often need to assess other firms, like competitors, suppliers, or acquisition targets. When assessing such firms, one can leverage our findings regarding firm type's moderating effect to inform one's judgment of a firm's AI adoption potential. Such informed judgments might also prove valuable information when forming partnerships in a business network aiming to combine the advantages of different firm types (Steiber & Alänge, 2020).

## Limitations and future research directions

Like any study, this study has several limitations that suggest potential paths for future research: The executives self-reported every skill and competency retrieved from the professional social network. Hence, executives may have exaggerated their qualifications to appear more qualified online. This potential bias is not specific to professional social networks. Executives might also exaggerate their skills in offline CVs or the information firms publish about their executives on their websites. Future research should develop study designs that allow the usage of measurement tools that do not depend on self-reporting. For instance, researchers could use measurements, such as micro-certifications, other verified skills, or tests. We also encourage future research to develop reliable and stakeholder-specific objective measurements for AI literacy. Subsequently, studies could apply these tools to mitigate potential biases due to self-reporting or to compare executives' subjective and objective AI literacy.

For this study, we leveraged an established taxonomy of 71 AI skills and competencies (Alekseeva et al., 2021) (Appendix A). However, the taxonomy also includes broad terms, such as "artificial intelligence" or "machine learning." One limitation of the analysis is that one cannot know what an executive refers to when they list "artificial intelligence" in their online profile. Therefore, we encourage future research to explore the breadth and depth of AI literacy of executives with more qualitative research designs. An executive-specific AI literacy taxonomy might pose a promising research direction with high practical relevance. Furthermore, such research could combine the role-oriented and skill-oriented perspectives on executives. Even though we emphasize the importance of the skill-oriented perspective in this study, executive roles are certainly still purposeful and will not vanish. Hence, it is of great interest how executive AI literacies for different executive roles should be composed.

This study used firm type as a moderating factor. Firm type contains valuable information on typical organizational resource configurations of firms that are rather established compared to rather new ventures (e.g., Andries et al., 2013). Such a distinction is of great practical relevance to executives because it can give concrete advice based on the firm they manage. However, firm type also simplifies the different organizational resources by assuming typical resource configurations, such as agile culture and fewer available financial resources within startups. Future research could investigate these relationships more explicitly by collecting individual information on the organizational resources of interest. Recent management research started using methods such as qualitative comparative analysis (e.g., Leppänen et al., 2023), which can identify specific configurations of variables that lead to certain outcomes. We urge further research to explore such methods in this context.

This study focused explicitly on *HR-related* AI implementation ability. Human resources are one and arguably the most critical factor in implementing AI (Jöhnk et al., 2020; Mikalef & Gupta, 2021). However, there are further factors that the research design of this study did not capture, such as IT or intangible resources (Weber et al., 2022). Future research should investigate these factors. For instance, studies could develop measurement methodologies for IT or intangible resources relevant to AI implementation ability. Furthermore, this study's *HR-related* AI implementation ability could be compared to *IT-related* or *intangible-related* AI implementation abilities.

## Conclusion

This study investigated how executives can facilitate AI orientation and HR-related AI implementation ability. It proposed the AI literacy of a firm's TMT as a novel predictor of the firm's AI orientation and HR-related AI implementation ability, which are two crucial steps to adopting AI. The results support that TMT AI literacy is associated with greater AI orientation and HR-related AI implementation ability, which extends prior AI upper echelons research with a skill-oriented perspective on TMTs. Furthermore, we find that AI orientation mediates TMT AI literacy's effect on HR-related AI implementation ability. This supports the claim that AI orientation is not an end in itself ("a strategy paper tiger") but that it leads to tangible change in the firm. Furthermore, the partial mediation shows that TMT AI literacy is distinctly associated with HR-related AI implementation ability, underlining its relevance for the firm. Lastly, we show that a startup's environment amplifies the effect of TMT AI literacy on HR-related AI implementation ability, giving practitioners valuable insights for AI management.

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